How does Business Analytics contribute to business value in organisations?

A thesis submitted in partial fulfilment of the requirements for a Master of Commerce in Information Systems

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Te Whare Wānanga o Waitaha

Abstract:

With the growing use of business analytics (BA), organisations have benefited from new ways to extract value from data and drive strategic, evidence-based decision making. However, much less thought about *how* Business Analytics contributes to business value in organisations has been given. We have conducted an in-depth qualitative study of fourteen semi-structured interviews of positions integral to BA within organisations using five value drivers and inhibiting factors that surround value generation.

As the research on business analytics completes its first decade, there is an opportunity to take a retrospective look at what has been done, and how well this compares to the practice of business analytics. This study had the objective of bridging the current knowledge gap through providing a holistic view of all five value factors and how they affect value generation. In order to answer the research question of "How does Business Analytics contribute to business value in organisations?". Specifically does Business value (BV) result in better informed evidence-based decisions? Through an after-action review (AAR), businesses are able to measure a decision's impact within an organisation.

The results of this study can be used by the managers of firms creating implementation strategies, as well as by other players in the ecosystem for analysing business analytic solutions. As well as identifying in what ways business analytics contributes to business value through developing a value framework.

Keywords: Business Analytics, Business Intelligence, Competitive advantage, Business Value of Information Technology

Contents

Abstract: **2**

Table of Figures **4**

Chapter One: Introduction **5**

1.1 Business Analytics vs Data Analytics: A comparison and Key Terminology 6

1.2 DIKW Pyramid: (Data, Information, Knowledge and Wisdom) 7

1.3 Thesis Outline: 9

Chapter Two: Literature Review **10**

2.1 Review Methodology: 10

2.2 Searching the scholarly literature: 10

2.3 Screening for Inclusion and Extracting Data: 13

2.4 Analysing and synthesising recent scholarly research: 13

2.5 Synthesis: 16

2.6 Theoretical Model 19

Chapter Three: Research Design and Method **21**

3.1 Data Collection: 21

3.2 Data Analysis: 23

3.3 Quality Assurance: 23

3.4 Ethical Considerations: 24

Chapter Four: Results and Analysis **27**

4.1 Word Frequency Analysis: 27

4.1 Thematic Analysis: 29

4.2 Thematic Analysis of Literature: 30

4.3 Thematic Analysis of Research Participants: 34

4.4 Value Driver Corroboration and Gap Analysis: 35

4.6 Value Inhibitors 39

Chapter Five: Findings and Discussion **41**

5.1 Practice Definition of Business Analytics 41

5.2 Data Assets 41

5.3 Human Capabilities 42

5.4 Business Analytics Impacts 44

5.5 Business Analytics Operations 45

5.6 Organisational Factors 46

Chapter Six: Conclusions **49**

6.1 Theoretical Contributions: 50

6.2 Implications for Practice: 51

6.3 Limitations: 52
6.4 Future Research: 52
6.5 Concluding Remarks: 53
References: 54
Annex A: Research Invitation and Interview Template 65
Annex B: HEC Approval 68
Annex C: Thematic Word Clouds 69
Annex D: Literature NVivo Analysis 71

Table of Tables

Table 1: Review Process 11
Table 2: Recent Scholarly Articles 13
Table 3: Scholarly Review of Synthesising Concepts 18
Table 4: Research Participants with Job titles 23
Table *5*: Research template used to guide the interviews. 25
Table 6: Top 10 Recent Literature Papers 27
Table 7: Most Frequent Words Used, Literature vs Industry: 29
Table 8: Least Frequent Words Used, Literature vs Industry: 29
Table 9: Tabulation of thematic results from literature 33
Table 10: Tabulation of thematic results of practitioner interviews. 35
Table 11: Summary of these results from the analysis of the definition. 36
Table 12: Corroborations and Gaps between Research and Practice 38
Table 13: Tabulation of Value Inhibitors and Themes. 40
Table 14: Highlights of the research findings 48
Table 15: Synopsis of Business Analytic Value Drivers 49
Table 16: Synopsis of Business Analytic Value Inhibitors 50

Table of Figures

Figure 1: A Historical view of the evolution of Analytics 6
Figure 2: Business Analytics Methods Framework 7
Figure 3: Adapted DIKW Pyramid 7
Figure 4: Procedure for Conducting Literature Reviews 10
Figure 5: Diagram of Paper Selection Process 11
Figure 6: Business Analytics Value Factors 17
Figure 7: Revisiting the Resource Orchestration Framework 19
Figure 8: Flowchart of Research Steps 26
Figure 9: Current Literature Word cloud (Left), Industry Word cloud (Right) 28
Figure 10: Example of NVivo Thematic Analysis. 31
Figure 11: Business Analytics Value Generation Model 51

Chapter One:

Introduction

Business analytics (BA) and business intelligence (BI) are both prominent IS areas which are experiencing rapid growth (Roy et al., 2020). With the quick development of artificial intelligence as well as developing concepts such as 'big data', business analytics and business intelligence. This area in Information Systems is becoming a topic of growing importance for both researchers and industry (Chen et al., 2012). BA can be defined as "the use of data to make sounder, more evidence-based business decisions" (Holsapple et al., 2014, p. 133). In a survey conducted by IBM Institute for Business Value and MIT Sloan Management Review, it was pointed out that increasingly firms are reporting a growth in competitive advantage through the use of analytics (Kiron & Shockley, 2011). Inside this report, 58% of more than 4500 respondents reported competitive value gains from analytics (Božič & Dimovski, 2019; Kiron & Shockley, 2011). As the definition suggests, the use of BA and BI tools by managers primarily aims at taking advantage of the numerous sources of available data and information to enhance decision making within organisations (Caya & Bourdon, 2016). In a survey of nearly 3,000 executives, managers and analysts working across more than 30 industries and 100 countries, top-performing organisations were found to be use analytics five times more than lower performers. These top-performing organisations also have substantial experience in harnessing BA and BA to create value (LaValle et al., 2011) With growing interest in this field, as well as the ever-growing need and the uptake of business analytics, comparatively little research has been undertaken to find out how BA creates value and competitive advantage within organisations (Delen & Ram, 2018; Grover et al., 2018; Seddon et al., 2017).

This thesis addresses such a research gap, more specifically it poses the following research question "How does Business Analytics contribute to business value in organisations?" as well as looking into what ways can BA create value and develop an understanding as to what factors influence this?

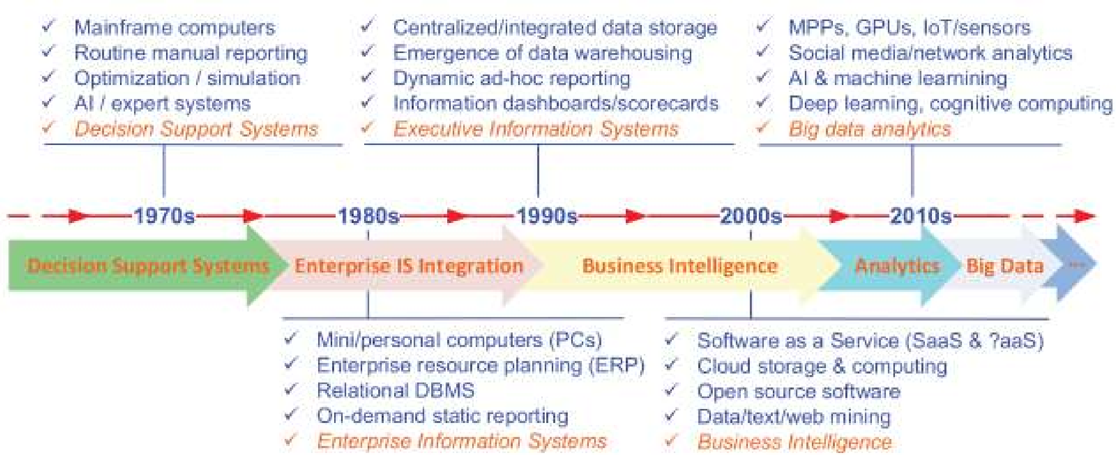
Prior studies have explored the compelling pathways which link value generation from business analytics, through insights and decisions, to increased organizational benefits (Seddon et al., 2017; Sharma et al., 2017). Meanwhile, the elements of a successful business analytics implementation have been recognized for reshaping operational capabilities and generating economic value, including BA infrastructure and functionalities, e.g. (Cao & Duan, 2014; Trkman et al., 2010; Wang et al., 2019; Wixom et al., 2013), analytical people (Tamm et al., 2013), data governance (LaValle et al., 2011; Tamm et al., 2013), information quality (Côrte-Real, Ruivo, Oliveira, et al., 2019), data-driven decision-marking culture (Cao & Duan, 2014; Kiron & Shockley, 2011).

1.1 Business Analytics vs Data Analytics: A comparison and Key Terminology

Although data has been hailed as the oil that power the 4th industrial revolution (Schwab, 2016), what makes data a valuable asset is the useful information hidden inside, which contains insight. Insight generation often requires different analytical techniques to find, which is either categorised and Data or Business Analytics.

Data analytics is the all-encompassing term for any analysis on any type of data. As such, data analytics can be widely applied to almost any area; it has abundant applications in business, with benefits stemming from recognising patterning in a dataset and making accurate predictions based on events. Differing from this business analytics focuses on identifying trends in an organisation that can be optimised to improve overall business planning and performance. Which in turn supports continuous improvement in technology and processes which seeks to arrive at a single source of truth (Duan & Xiong, 2015).

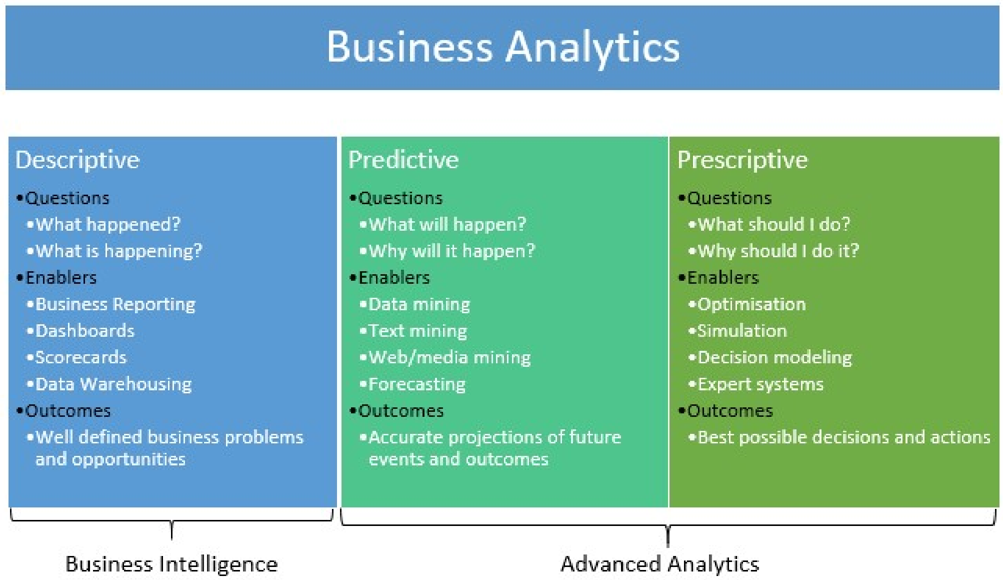
Figure 1: A Historical view of the evolution of Analytics



Adapted from: (Delen & Ram, 2018)

There are three types of data analytic methods which are descriptive analytics, predictive analytics and prescriptive analytics. Descriptive analytic methods are used to understand what has happened in the data regarding its key indicators. Descriptive analytics is used to understand the reasons behind past success or failure. It is the first stage of data analytics and still the majority of the current business analytics applications. The next stage of data analytics is predictive analytics, which can be used to forecast future events based on past patterns. The final stage is prescriptive analytics, which uses optimization and other mathematical models to identify the best actions and decisions as well as to benchmark the efficiency of implementing such action.

Figure 2: Business Analytics Methods Framework

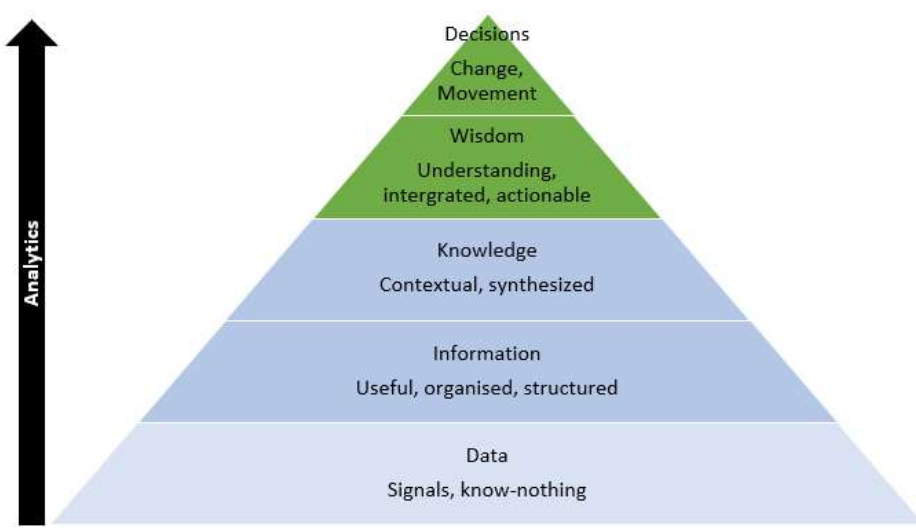


Adapted from: (Appelbaum et al., 2017, p. 32)

1.2 DIKW Pyramid: (Data, Information, Knowledge and Wisdom)

The hierarchy outlined below is used to contextualise data, information, knowledge, and wisdom/ decision making, with respect to one another and to identify and describe the processes involved in the transformation of an entity at a lower level in the hierarchy (e.g. data) to an entity at a higher level in the hierarchy (e.g. information). The implicit assumption is that data can be used to create information; information can be used to create knowledge, and knowledge can be used to create wisdom, which in turn leads evidence based decision making within the business (Ackoff, 1989; Ahsan & Shah, 2006; Hey, 2004; Jennex, 2009; Rowley, 2007).

Figure 3: Adapted DIKW Pyramid



Adapted from: (Lokshina & Lanting, 2019)

A further elaboration by (Ackoff, 1989) is as follows…

Data is raw. It simply exists and has no significance beyond its existence (in and of itself). It can exist in any form, usable or not. It does not have meaning of itself. In computer parlance, a spreadsheet generally starts out by holding data. Davenport and Prusak (1998, p. 2) state that "Data is a set of discrete, objective facts about events…Data describes only a part of what happened; it provides no judgment or interpretation and no sustainable basis of action…Data says nothing about its own importance or relevance."

Information is data that has been given meaning by way of relational connection. This "meaning" can be useful but does not have to be. In computer parlance, a relational database makes information from the data stored within it. Davenport and Prusak (1998, p. 3) state that "Data is a set of discrete, objective facts about events…Data describes only a part of what happened; it provides no judgment or interpretation and no sustainable basis of action…Data says nothing about its own importance or relevance."

Knowledge is the appropriate collection of information, such that its intent is to be useful. Knowledge is a deterministic process. Davenport and Prusak (1998, p. 5) maintain that "knowledge derives from information as information derives from data". They view knowledge as refined information, in which human cognition has added value. Information becomes knowledge through cognitive effort. For example, the human mind can compare information about a specific situation with other situations it has known, anticipate implications for decisions and actions, relate one bit of knowledge to other bits of knowledge, and share interpretations with other people (Ahsan & Shah, 2006).

Wisdom is an extrapolative and nondeterministic, non-probabilistic process. It calls upon all the previous levels of consciousness, and specifically upon special types of human programming (moral, ethical codes, etc.). In short we can define wisdom as the application of intelligence and experience toward the attainment of a common good (Ahsan & Shah, 2006).

1.3 Thesis Outline:

Chapter One: Introduction

The first chapter introduces the research by providing an overview of business analytics, as well as the importance and relevance of the research topic and gaps within the subject area. This also introduces key research questions and the objectives of this research.

Chapter Two: Literature Review

The second chapter presents current previous research within the field of Business Analytics, providing a foundation for the extended focus on Value factors. First the development of the research area is explained, thereafter the need for more exploration is highlighted.

Chapter Three: Research Design and Methodology

The first part of this chapter proposes the modified research model, based on the Information Systems Resource Orchestration theory and developed further by (Božič & Dimovski, 2019) and (Seddon et al., 2017). This model was subsequently used as a foundation and a guiding tool during data collection.

Secondly this chapter introduces the methodological approach, which has been applied for this study. Further, it includes design approach, research approach, interview and the method for analysis. To conclude the chapter, we elaborate on the qualitative assurance and ethical considerations.

Chapter Four: Results and Analysis

The fourth chapter presents the findings from the 14 semi-structured interviews, who provided in-depth answers to the questions outlined in the interview template. This chapter also includes both thematic and word frequency analysis to uncover key themes within the interviews.

Chapter Five: Findings and Discussion

In this chapter, the analysis of the qualitative findings in conjunction with the theoretical background is presented. As this study investigates, “How does Business Analytics contribute to business value within organisations?” the analysis and discussion are centred around a wider-reaching lens. Further, this chapter concludes by summarising the findings, meanwhile also providing an extended discussion regarding the qualitative findings and what implications they have in terms of research.

Chapter Six: Conclusions

Lastly, this chapter outlines the theoretical and practical implications of the findings derived from this research, followed by limitation and suggestions for future research.

Chapter Two:

Literature Review

This chapter presents current previous research within the field of Business Analytics, providing a foundation for the extended focus on Value factors. First the development of the research area is explained, thereafter the need for more exploration is highlighted.

2.1 Review Methodology:

For this literature review, we used a framework developed by (Templier & Paré, 2015). The following framework is structured as follow, Formulating the problem, Searching the literature, Screening for inclusion, Assessing quality, Extracting data and Analysing and synthesizing data.

Figure 4: Procedure for Conducting Literature Reviews

Formulating the problem

- This step requires authors to define the review's objective(s),provide definitions of key concepts and justify the need for a review article.

Searching the literature

- This is the beginning of the data collection phase. At this time, authors must identify a range of information sources as well as the studies that are pertinent to the review.

Screening for inclusion

- The next step of the data collection phase includes evaluating the applicability of the studies previously identified and selecting or excluding them.

Assessing quality

- This step involves assessing the methodological quality of the primary studies.

Extracting data

- This step involves gathering applicable information from each of the primary studies included in the review.

Analysing and synthesising data

- This last step requires authors to organize, compare, collate, summarize, aggregate or interpret the information previously extracted in order to suggest a new contribution to knowledge.

Adapted from: (Templier & Paré, 2015, p. 6)

2.2 Searching the scholarly literature:

In this phase, work was done to identify potentially relevant studies. Numerous databases were searched including Google Scholar, Scopus and the University of Canterbury's own Multisearch. These databases were searched with queries containing terms such as 'business analytics business value, business analytics value, business analytics value creation, business analytics competitive advantage'. The search of these platforms completed a search for the “Title”, “Abstract” and “Subject” for pertaining conferences. Not all papers would have the search queries within the title, topic, abstract or subject, however, would still be relevant to the review. Because of this, additional search queries such as ‘business analytics’ and ‘data-driven’ were included in the review (Boell & Cecez-Kecmanovic, 2015). The search was conducted on a broader level, using a phased approach, expanding as themes were discovered. To minimise the risk of publication bias dissertations and conference proceedings were also included in the search (Templier & Paré, 2015). The majority of papers that met this criterion appeared to primarily originate from IS-related sources, indicating that this discussion resides in the IS community for the most part.

Figure 5: Diagram of Paper Selection Process

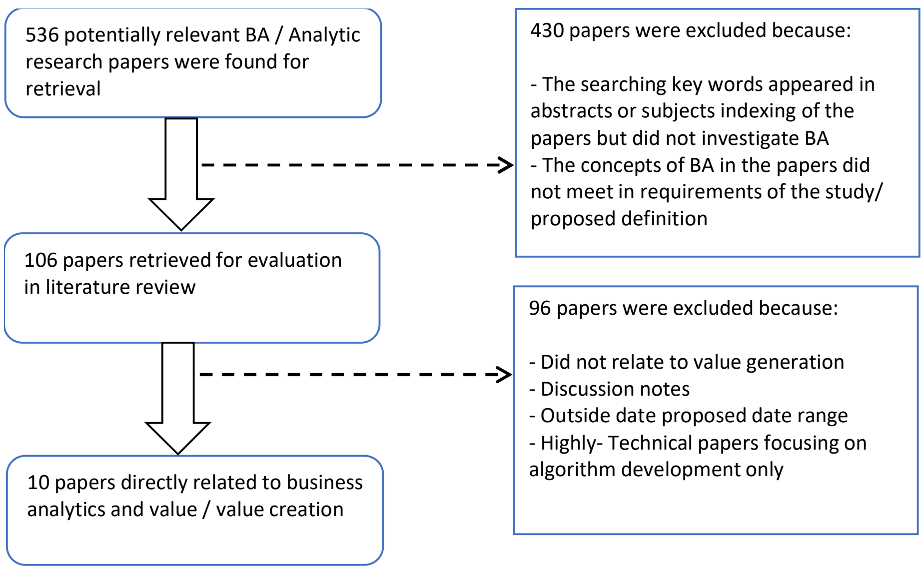


Table 1: Review Process

Year of Publication	1/2006–1/2020
Keywords	“Business analytics business value”, “Business analytics value”, “Business analytics value creation”, “business analytics competitive advantage”, “business analytics” and “data-driven”
Journals	• European Journal of Information Systems (EJIS) • Information Systems Journal (ISJ) • Information Systems Research (ISR) • Journal of Association for Information Systems (JAIS) • Journal of Information Technology (JIT) • Journal of Management Information Systems (JMIS) • Journal of Strategic Information Systems (JSIS) • MIS Quarterly (MISQ) • Decision Support Systems (DSS) • Highly cited papers from other journals (HCP)
Search engines and databases	Google Scholar, Scopus and the University of Canterbury’s own Multisearch

Resulting from this, many studies were found to be contributing to this knowledge in different ways. Stemming from this, some seminal studies that were found during this stage are presented (Templier & Paré, 2015).

In a research paper titled 'Pathways to value from business analytics' by Tamm et al. (2013), it investigated what pathways BA contributed to business value, through exploring different types of BA use in terms of tools and capabilities. This led to the identification of two main types of BA users, which were categorised as either analytics professionals or analytics end-users. This led to the classification of three 'pathways to value from business analytics' which were "provision of advisory services, creation and enhancement of BA tools and the BI-platform and use of BA tools by end-users." Tamm et al. (2013, p. 1). Which (Tamm et al.) verified through conducting eleven one-hour interviews with thirteen senior managers with a wide range of interests in BA.

In a paper published by the Information System Journal, Seddon et al. (2017) looked into developing a business analytics success model (BASM). This comprised of five factors from Davenports DELTA model of business analytics success factors (Davenport et al., 2010), six from Watson & Wixom and three from Seddon's model of organisational benefits. A preliminary assessment of the model was conducted using data from 100 customers success stories from prominent BA vendors such as IBM and SAP. This research was completed with the aim to provide managers with a clearer understanding of how an organisations BA capability can influence organisational performance. This paper was concluded with the "hope that other researchers will be able to take and extend our ideas and conduct further tests of the BASM or similar models." Seddon et al. (2017, p. 266).

In a paper published by the Journal of Data & Knowledge Engineering. Nalchigar and Yu (2018) looked to develop a framework for requirements analysis and design of data analytics systems. This framework encompassed three modelling views which were business view, analytics design, and data preparation. In order to validate this framework (Nalchigar & Yu) illustrated the usability through testing this against three data analytics case studies. "This was done with the purpose of finding how to use analytics to derive value and gain a competitive advantage" Nalchigar and Yu (2018, p. 1).

In a recent paper published by the International Journal of Information Management, Božič and Dimovski (2019) looked into business intelligence and analytics for value creation. In this study, fourteen in-depth, semi-structured interview over a sample of informants such in CEO, IT managers, Heads of R&D, as well as Market managers across nine medium to large firms, were conducted. The studies suggest that it might be insufficient to focus on improved decision making that stems from BA, without considering how knowledge creation occurred in the first place. With the findings also shedding light on how knowledge is created from BA and BI triggered insights.

Table 2: Recent Scholarly Articles

Author, Year	Title	Key Findings
Tamm et al. (2013)	Pathways to value from business analytics	Two key types of Analytic users either analytics professionals or analytics end-users.
Seddon et al. (2017)	How does business analytics contribute to business value?	Creation of the BASM (Business Analytic Success Model)
Nalchigar and Yu (2018)	Business-driven data analytics: A conceptual modelling framework	Development a framework for requirements analysis and design of data analytics systems
Božič and Dimovski (2019)	Business intelligence and analytics for value creation: The role of absorptive capacity	Sheds light on how knowledge is created from BA and BI triggered insights

2.3 Screening for Inclusion and Extracting Data:

Based on the described procedure, the initial pool consisted of over 100 potential candidates. From this, papers from the pool where codified into key themes. These papers resulted from the "Searching the literature" phase and qualified for inclusions as they discuss how a business can utilize business analytics to create business value, 'business analytics business value, business analytics value, business analytics value creation, business analytics competitive advantage' or secondary search terms.

From these ten papers were found that related directly to business analytics and value/value creation. (Chiang et al., 2018; Isson & Harriott, 2012; Krishnamoorthi & Mathew, 2015; Seddon et al., 2017; Someh & Shanks, 2013; Tamm et al., 2013; Vidgen et al., 2017; Wang et al., 2019; Wixom et al., 2013; Yoo & Roh, 2018)

2.4 Analysing and synthesising recent scholarly research:

The analysis focuses on summarising and analysing existing theories as to how business analytics can contribute to business/organisational value. This section focused on highlighting prevailing debates related to this topic while identifying supporting evidence and gaps in the literature (Jones & Gatrell, 2014; Templier & Paré, 2015). Through reviewing these papers, key themes were found as to how organisations realise value from business analytics.

The first being BA/ Data assets. Out of the papers reviewed BA assets is a necessary condition that must be present for a firm to achieve BA value. Such as developing insight, forming new products or idea, leading new strategies, redesigning business process, more informed decision making and process improvement (Soh & Markus, 1995). Assets can consist of a wide range of resources such as organisation processes, a firms attributes, information knowledge, "which is able to be utilised by a firm to enable it to conceive of and implement strategies that improve its efficiency and effectiveness" Barney (1991, p. 101). It is also pointed out that any resource/asset is able to bring an organisation value if it is able to change the way that an organisation is able to capture opportunities or nullify threats and is hard for competing organisations to imitate. Displaying that assets can exist as physical, financial or human. (Barney, 1991) states that these assets, however, do not provide a competitive advantage to the organisation unless they are valuable, rare, inimitable, and non-substitutable. (Seddon et al., 2017) points out that BA assets include people who are needed for analysing information and are embedded in many places throughout the focal organisation.

According to (Côrte-Real, Ruivo, & Oliveira, 2019) BA applications can be accelerated through the implementation of a robust IT infrastructure. This is also benefited through a data-oriented culture to ensure that BA and BI are included in business processes to improve their performance (Watson, 2014). Consequently, BA assets are most often acquired pre-packaged from BA vendors such as IBM and SAP, that contain built-in applications and functionalities (Nalchigar & Yu, 2020). This is then integrated into an organisation existing decision-making routine in various functional activities. “The knowledge of how to use these applications is transferred from the BA vendor to BA business users through the support from BA technical staff.” (Wang et al., 2019, p. 4). Furthermore, in terms of BA assets the results illustrate that high-quality BA tools are able to be attuned, when combined with the matching hardware infrastructure to quickly churn large amounts of data (Capellá et al., 2012; Trieu, 2017). In the same way, an emphasis is put on the quality of the hardware, which is a critical factor in making BA a viable tool for decision making during uncertainty (Di Domenica et al., 2007). In today’s climate businesses are moving away from high upfront investment towards higher scalability ‘pay per usage’ monthly cloud-based services. Such as ‘Software as a Service’, business intelligence as a service, analytics as a service, and software on demand (Acito & Khatri, 2014). With these services being offered from vendors such as IBM with their “Mart Analytics System” and Amazons analytics service “Amazon Cloud” (Zorrilla & García-Saiz, 2013). On the same theme (Ylijoki & Porras, 2018) claim that the quality of BA tools and hardware is one of the factors that can help managers successfully generate value through BA asset investment.

Another essential point is the Human Capabilities part of BA assets. Employees that are trained to work with analytics, and skilled to decode output are highlighted as critical assets that enable organisations to realise business value (Božič & Dimovski, 2019; Culumber, 2017; Lamba & Dubey, 2015; Leon et al., 2018; Sharma et al., 2007; Stevens, 2017; Tamm et al., 2020; Wang et al., 2019). According to (Tamm et al., 2013), there are two distinct types of BA users. The first being an “Analytics Professional” who are typically skilled individual’s such as “business analysts” or “data scientists”. Stating that “Typically, they provide evidence-based insights on a range of structured and unstructured questions to organisations more senior managers.” (Tamm et al., 2013, p. 3). The second type that was categorised is an “Analytics End-User”. These are employees within the organisations who are affected by the outcomes of “Analytics Professionals”. However “Such people typically have good business knowledge, but frequently do not have strong statistical or analytic skills.” (Tamm et al., 2013, p. 3). Many studies have suggested that an organisation's human resources are a vital driver for BA success (Côrte-Real, Ruivo, Oliveira, et al., 2019; Grevler, 2017; Holsapple et al., 2014;

Seddon et al., 2017; Tamm et al., 2013; Trkman et al., 2010; Wang et al., 2019). Because of this organisations are encouraged to combine analytical talents with other skills of employees in the pursuit of more significant business results. (Leon et al., 2018; Trieu, 2017). “Again, it is important to point out that insight occurs in people’s heads, not in computers, and that they are possibly erroneous interpretations of reality.” (Seddon et al., 2017, p. 249). In summary of the literature, there is a suggestion that a strong focus in high-quality BA assets, with an emphasis on human resources, is overall favourable towards BA business value.

The second is BA impacts. BA Impacts is a necessary condition that must be met for value creation and improve performance for an organisation (Elbashir et al., 2008). These impacts can extend across an organisation. Ranging from improved performance and operational efficiency, process alignment, expansion to new markets, targeted/improved products and services and competitive advantage (Bronzo et al., 2013; LaValle et al., 2011; Lim et al., 2013; Ransbotham et al., 2016; Shanks et al., 2010; Trieu, 2017; Trkman et al., 2010; Yoo & Roh, 2018). According to Shanks et al. (2010, p. 5) impacts can be felt in an organisation through “using insight gained from analysing data, organisations might launch new products, develop new products, introduce differential pricing, or create new channels for customer interaction.” The findings indicate that BA can have an impact in organisational areas such as “in Plan”, “in Source”, “in Make” and “in Deliver” (Trkman et al., 2010). It has been shown through studies that BA impacts can improve an organisation's operational efficiency through targeting correct customers and clientele, transforming business process, enhancing organisational intelligence and more informed development of products and services (Acito & Khatri, 2014; Trieu, 2017).

The third is BA Operations. The literature recognises BA operations as BA processes, work practices, and routines performed within the organisation (Davenport et al., 2010; Wang et al., 2019). BA operations also encompasses BA expertise. Which is the technical knowledge of how to maintain the BA data infrastructure and to develop, use, and implement BA applications as well as a general understanding of trends related to BA technologies. (Vidgen et al., 2017; Wang et al., 2019). In order for a BA implementation to reach its maximum benefit, it has to be able to be used efficiently and effectively (Burton-Jones & Grange, 2012). Along the same lines, for an organisation to reap the maximum benefits for a BA system, the system must be used both efficiently and extensively. Hence the literature suggests it must be integrated into the core of the organisation. However, these systems, when used ineffectively, may negatively impact the task performance of both the individual user and the organisation (Deng & Chi, 2012; Seddon et al., 2017).

Additionally (Harris & Davenport, 2007; Shanks et al., 2010) propose three tiers of operational levels depending on what the firm aims to achieve with business analytics. This takes into account the extent that business analytics is implemented within the firm, at an organisational and enterprise level. The first tier describes “Localised analytics”. At this level, functional management within the organisation builds analytics momentum and executive interest through the use and application of basic analytics. The second tier is

“Analytical companies” This is where enterprise-wide analytics are deployed, where top executives place analytic capability as a priority. The final tier is “Analytical competitors” This is where “organisations routinely reap the benefits of their enterprise-wide analytical capability and focus on continuous analytics renewal” (Shanks et al., 2010, p. 9). It is subsequently noted that organisations will progress through there three tiers as BA assets and focus develops over time. This reflects the view that BA operations per se cannot bring benefits unless it reflects the viewpoint and focus on the organisation. (Nevo & Wade, 2010; Shanks et al., 2010; Trice & Treacy, 1988)

The fourth is Organisation factors. Numerous studies investigated how factors about the organisation can contribute to BA business value (Božič & Dimovski, 2019; Buldoo, 2018; Cao & Duan, 2014; Grevler, 2017; Lamba & Dubey, 2015; Shanks et al., 2010; Stevens, 2017). Factors such as organisational size, scope and absorptive capacity were noted to assist with the successful adoption and use of BA. Stemming for this the (Soh & Markus, 1995) suggests that the size of the organisation will determine the ability that they can convert BA assets into BA impacts. Besides (Buldoo, 2018; Ramamurthy et al., 2008) suggest that larger organisations can exploit BA’s potential to a greater extend, compared to smaller organisations, which was reiterated by (Akter et al., 2016; Cosic et al., 2012) who found that the size of the organisation is a significant factor in BA exploitation. Several studies noted an organisations absorptive capacity level acts as a mediating role in the link between BA performance and business performance (Gao et al., 2017; Wang et al., 2019; Yoo & Roh, 2018). In summary, the literature in this area suggests that Organisational factors such as the size of the organisation and absorptive capacity, being the firm’s ability to recognise, assimilate and transforms BA output are favourable towards BA business value.

2.5 Synthesis:

To synthesise the scholarly literature on business analytics value realisation is scarce, with some repackaging of old ideas being present also. The focus of BI and BA research has been primarily technical, with the inclusion of specific domains such as supply chain efficiency (Krishnamoorthi & Mathew, 2015). This literature review has highlighted that there is currently a lack of research pertaining to business value, adoption and business process management. This review reveals key factors that support business analytics value creation, including factors such as BA assets, BA impacts, BA operations and organisational factors. Having analysed a substantial body of literature, it suggests that business analytics and business intelligence are both topics that are currently gaining traction globally, and of great interest to the business community (Larson & Chang, 2016). However, there is such a vast amount of different viewpoints and factors that it must be hard for managers, executives and organisations to decide what they need to do to realise value from BA (Seddon et al., 2017). For example, theoretically ‘value’ has been acknowledged as a key construct of IS Success (Delone & Mclean, 2004). Thus, there remains a need for a more in-depth analysis of the processes and factors that organisations require to receive value from BA, to allow for more efficient and effective uptake.

Figure 6: Business Analytics Value Factors

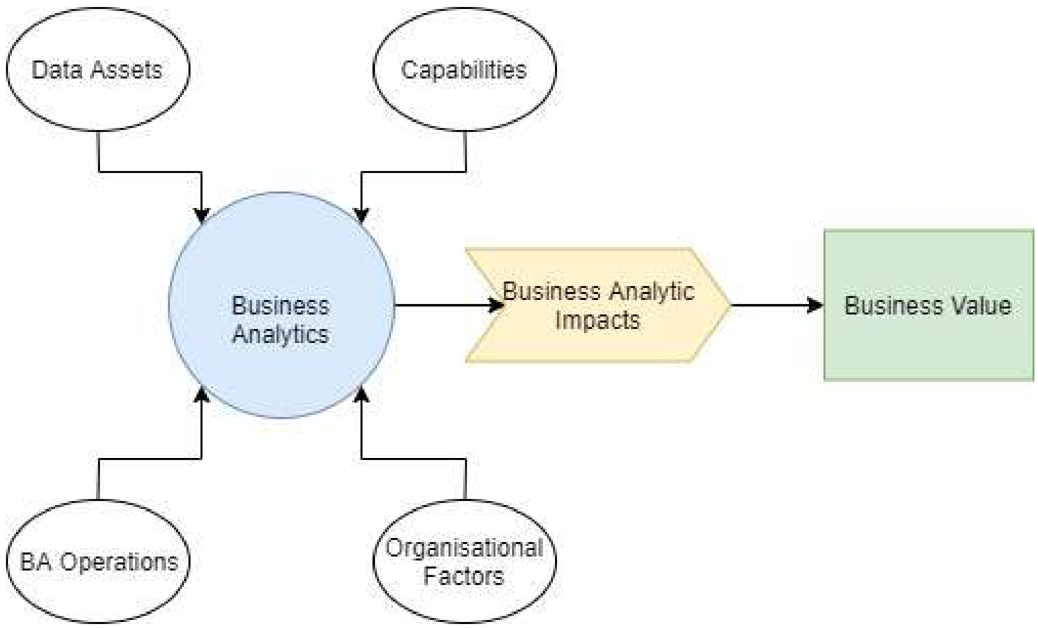


Table 3: Scholarly Review of Synthesising Concepts

Value Driver	Description	Supporting Literature
Data Assets	Analytics tools and packages from vendors such as IBM and SAP, hardware and infrastructure	(Acito & Khatri, 2014; Barney, 1991; Capellá et al., 2012; Côrte-Real, Ruivo, Oliveira, et al., 2019; Di Domenica et al., 2007; Nalchigar & Yu, 2020; Seddon et al., 2017; Soh & Markus, 1995; Trieu, 2017; Wang et al., 2019; Watson, 2014; Ylijoki & Porras, 2018; Zorrilla & García-Saiz, 2013)
Human Capabilities	Analytical training and skills to decode output into insight and decision making	(Božič & Dimovski, 2019; Côrte-Real, Ruivo, Oliveira, et al., 2019; Culumber, 2017; Grevler, 2017; Holsapple et al., 2014; Lamba & Dubey, 2015; Leon et al., 2018; Seddon et al., 2017; Sharma et al., 2007; Stevens, 2017; Tamm et al., 2013; Wang et al., 2019)
BA Impacts	Improved performance, operations efficiency, targeted products, process alignment and expansion in new markets	(Acito & Khatri, 2014; Bronzo et al., 2013; LaValle et al., 2011; Lim et al., 2013; Ransbotham et al., 2016; Shanks et al., 2010; Trieu, 2017; Trkman et al., 2010; Yoo & Roh, 2018)
BA Operations	Business Analytics processes, work practices and routines performed within the organisation to support BA use	(Burton-Jones & Grange, 2012; Davenport et al., 2010; Deng & Chi, 2012; Elbashir et al., 2008; Harris & Davenport, 2007; Nevo & Wade, 2010; Shanks et al., 2010; Trice & Treacy, 1988; Vidgen et al., 2017; Wang et al., 2019)
Organisational Factors	Organisational size, scope and absorptive capacity to assist with the successful adoption and use of BA.	(Akter et al., 2016; Božič & Dimovski, 2019; Buldoo, 2018; Cosic et al., 2012; Gao et al., 2017; Grevler, 2017; Lamba & Dubey, 2015; Ramamurthy et al., 2008; Seddon et al., 2017; Shanks et al., 2010; Soh & Markus, 1995; Stevens, 2017; Tamm et al., 2013)

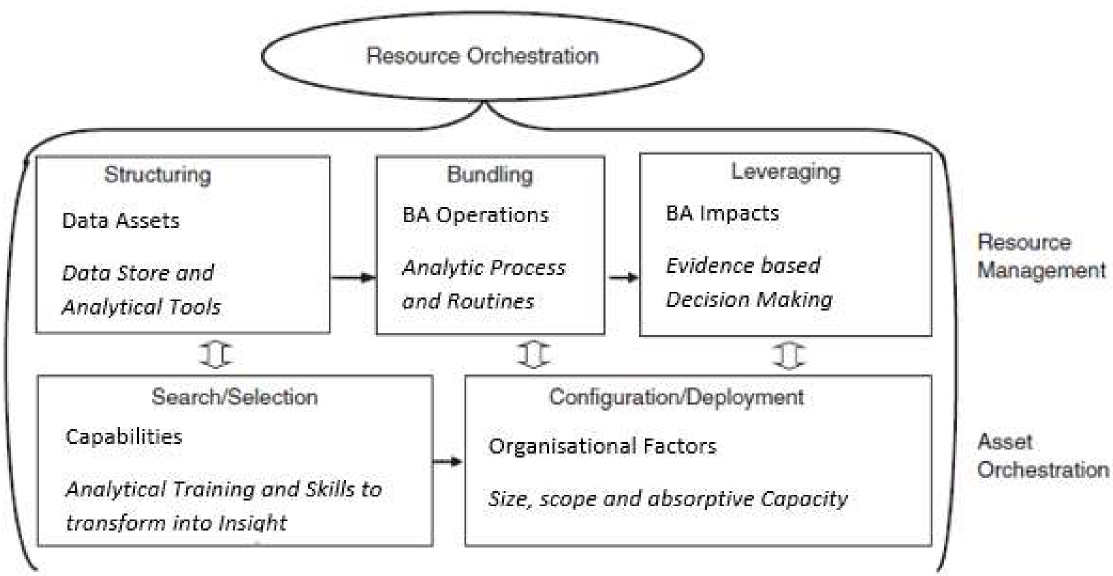
Table 3 led to the formulation of a theoretical research model for the purpose of developing an empirical data collection methodology.

2.6 Theoretical Model

This section proposes the modified research model, based on the Information Systems Resource Orchestration theory and developed further by (Božič & Dimovski, 2019) and (Seddon et al., 2017). This model was subsequently used as a foundation and a guiding tool during data collection.

Orchestrating resources is critical to developing and implementing a range of firm strategies. As such, in this section, we address the breadth of resource orchestration by examining its impact on and implications for corporate strategies, business strategies, and the competitive dynamics in industries (Sirmon et al., 2010). 'Resource orchestration' comprises of three stages: structuring, bundling and leveraging. The key insight that stems from resource orchestration is that organisations often differ systematically in the extent to which their process for transforming inputs into outputs lead to business value, with 'value' being defined in a resource orchestration context, as the amount that consumers are willing to pay for the organisations good or service and the organisations cost to produce and deliver that product (Yi Liu, 2019).

Figure 7: Revisiting the Resource Orchestration Framework.



Adapted from: (Sirmon et al., 2010, p. 1395)

This model formed conceptual scaffolding which was also tied with two pieces or prior research by (Seddon et al., 2017) and (Božič & Dimovski, 2019).

Seddon et al. (2017) looked into developing a business analytics success model (BASM). This comprised of five factors from Davenports DELTA model of business analytics success factors (Davenport, Harris, & Morison, 2010), six from Watson & Wixom and three from Seddon's model of organisational benefits. A preliminary assessment of the model was conducted using data from 100 customers success stories from prominent BA vendors such as IBM and SAP. This research was completed to provide managers with a clearer understanding of how an organisations BA capability can influence organisational performance. This paper was concluded with the "hope that other researchers will be able to take and extend our ideas and conduct further tests of the BASM or similar models." (Seddon et al., 2017, p. 266).

Following (Božič & Dimovski, 2019) looked into business intelligence and analytics for value creation. In this study, fourteen in-depth, semi-structured interview over a sample of informants such in CEO, IT managers, Heads of R&D, as well as Market managers across nine medium to large firms, were conducted. The studies suggest that it might be insufficient to focus on improved decision making that stems from BA, without considering how knowledge creation occurred in the first place. With the findings also shedding light on how knowledge is created from BA and BI triggered insights.

Through synthesising the findings from these two researchers in conjunction with the research orchestration model form a lens in which will be used to form the basis and empirical context for which will be used to explain theoretical conclusions from our research. The present study probes deeper into the orchestration of assets and capabilities in order to answer the question of how value is derived from analytics.

In the empirical part of the thesis this theoretical research model served two purposes in developing a structural interview template (SIT).

1. It addressed the key question of how Business analytics impacts Business Value?
2. It further delved into the structuring, bundling and leveraging aspect of the BA value chain.

The structural interview template may be found in Annex A.

Chapter Three:

Research Design and Method

This chapter introduces the methodological approach, which has been applied for this study. Further, it includes design approach, research approach, interview and method for analysis. To conclude the chapter, we elaborate on the qualitative assurance and ethical considerations.

As found within the literature review, the area of data and business analytics within the IS field is new, broad and sophisticated, making it challenging to identify casual relations. Taking into account that the relevant literature on business analytics value realisation is scarce for this research we built upon the research of (Božič & Dimovski, 2019) and (Seddon et al., 2017). In order to answer the research question, this study was designed using an exploratory qualitative approach. We apply abductive scientific reasoning (Baker & Edwards, 2012; Basit, 2003) where initial inductive insights from empirical data are engaged with existing theoretical knowledge to explain empirical findings. We assume the semi-structured interview to be the most effective method of gathering information for our research since is suitable when the interviewer needs a deeper understanding of a problem, as it allows for the opportunity to identify details, which in this case is favourable to grasp the complexity of the problem area (St. Pierre & Jackson, 2014; Weston et al., 2001). Furthermore, due to the aim of this research, the collection of in-depth data from various perspectives was needed, thereby a qualitative study was applied. Based on the ambition to gain multiple perspectives, the choice was made to include 14 interviews. This was in order to gain a deeper understanding of the business analytics perspectives by examining different companies, their solutions and implementations and further providing the opportunity to contrast the interviews, to explore potential similarities and differences (Weston et al., 2001).

3.1 Data Collection:

There are various ways in which data can be collected for qualitative research, including observations, focus groups and in-depth interviews (Bell et al., 2018; Braun & Clarke, 2006). For this study, the data was collected primarily using semi-structured interviews, with an interview template as a basis. Besides the flexibility of applying semi-structured interviews, it was also used due to the nature of the research question and the previous choice of adopting a hermeneutic perspective, as it is consequently commonly applied (Bell et al., 2018). Further, semi-structured interviews provide the researcher with rich contextual information regarding the respondent's experience as it allows for the interviewer to get a good understanding of the research area without influencing the interviewee with any preconceived notions (Bell et al., 2018). Additionally, it is a collection technique widely adopted in information system research (Schultze & Avital, 2011).

The interview guide mentioned earlier was developed by iterating the suggested guiding questions provided by Božič and Dimovski (2019). The final semi-structured interview guide included questions framed around value drivers uncovered from the literature, as well as general questions regarding the personal views of success of an implementation and inhibitors to value. The questions were broad and open-ended to allow respondents to freely discuss what they considered necessary when answering (Bell et al., 2018). Moreover, by utilizing this type of interview technique, it provided the ability to ask follow-up questions to add interesting ancillary considerations.

The semi-structed interviews were conducted in-person to ensure that rich and in-depth answers where gathered. Participants were contracted via email the day before each interview and provided with a copy of the interview template so that thoughtful and rich responses could be provided (Mays & Pope, 2020). Before each interview began, the interviewees were made aware of the essence of the research and asked to consent of the recording of the interview (Walsham, 2006). As all of the respondents accepted this, it allowed for the possibility to thoroughly listen and interpret their answer after the fact, as all interviews were transcribed. The participants were also assured of their anonymity in the thesis.

Further, when conducting qualitative interviews, one needs to be aware of the level of data saturation, related to the degree to which new responses repeat what has already been expressed previously (Saunders et al., 2018). In terms of the number of interviews needed, this depends from case to case. For this study, it resulted in 14 interviews. However, while additional ones could be perceived as beneficial, much empirical evidence had been repeated by the 14th interview, pointing to a clear indication of saturation (Baker & Edwards, 2012; Bell et al., 2018; Saunders et al., 2018). All the interviews had a duration of approximately 60 to 90 minutes.

According to the needs of this study, we selected fourteen expert interviewees (key informants) in positions within the variety of Business Analyst, Information Officer, IT manager roles. All of them possessed and actively used BI&A in their everyday work. To the extent feasible, the interviews were chronological arranged to begin at roles which were operationally/tactically focused to roles which were more high level and strategic, so that knowledge gained from earlier interviews could be expanded on. These interviews were conducted from the 21st of August 2019 through to 14th of October 2019.

Table 4: Research Participants with Job titles

Strategic Level

Respondent	Title	Degree of Experience with BI&A
1	General Manager of Information Technology	High
2	BI & Transformation Manager | Data and Analytics	High
3	Commercial Manager	High
4	Customer Analytics & Insights Manager	High
5	Business Analyst / IT Manager	High
6	Decision Support Manager	High
7	Business Intelligence Manager	High
8	Data Engineering Manager	High
9	Data Scientist Consultant	Moderate
10	Senior Business Analyst	Moderate
11	Senior Business Analyst	Moderate
12	Senior Business Analyst	Moderate
13	Business Analyst	Low
14	Business Analyst	Low

3.2 Data Analysis:

As the interviews with the participants were recorded and transcribed, this enabled thematic analysis to be conducted on the qualitative data in a structured and systematic manner (Basit, 2003; Bell et al., 2018; Leung, 2015). Braun and Clarke (2006) describe thematic analysis as "Thematic analysis is a method for identifying, analysing, and reporting patterns (themes) within data. It minimally organises and describes the data set in (rich) detail. However, it also often goes further than this and interprets various aspects of the research topic" (Braun & Clarke, 2006, p. 6). This research followed a more exploratory qualitative approach. We applied abductive scientific reasoning by identifying new trends in addition to verifying and extending existing theoretical knowledge uncovered. The coding was done using interviews using the semantic tool NVivo. NVivo has been selected as it is designed for qualitative researchers working with rich text-based data where deep levels of analysis is required and has thematic analysis capabilities (Bazeley & Jackson, 2013). Additionally, this analytical process allowed for the comparison of the derived findings with the outcomes of prior research and theory.

3.3 Quality Assurance:

Given the diverse genera and forms of qualitative research, the relevance and applicability of qualitative research have been contested, and this is no consensus for assessing any piece of qualitative research work (Leung, 2015; Mays & Pope, 2020; Pipino et al., 2002; Sargeant, 2012). From this various approaches have been suggested, the two leading schools of thoughts being the school of Dixon-Woods et al.

(2004) which emphasizes on methodology, and that of Lincoln et al. (2011) which stresses the rigour of interpretation of results.

To achieve credibility in the research findings, two main strategies were used to promote the rigour and quality, which were to ensure the “authenticity” of the data and the quality or “trustworthiness of the analysis (Sargeant, 2012).

3.3.1 Authenticity:

This strategy refers to the quality of the data and the data collection procedures which were used during the study. Firstly, included participant selection which was unbiased, through interviewing participants with a broad range of skill sets, top titles and positions within organisations (Kuper et al., 2008). Next Patton (2002) and Sargeant (2012) state that the appropriate method to answer research questions much be used. Semi-structured interviews were chosen as they provide the researcher with rich contextual information regarding the respondent’s experience as it allows for the interviewer to get a good understanding of the research area without influencing the interviewee with any preconceived notions (Bell et al., 2018), thus being appropriate for the study. The strategy supporting authenticity also requires the researcher to ensure that interviews undertaken in the study are not biased or leading. To ensure this an interview template was used within the study so that questions did not cause participants to answer in a particular manner, instead were used as a starting point for further in-depth discussion surrounding the topic.

3.3.2 Trustworthiness:

The second strategy surrounding quality assurance, trustworthiness refers to the quality of the data analysis undertaking within the study. While this has been outlined in the study in the paragraphs above in the data analysis section, trustworthiness in the data analysis played a vital role in the study, hence why steps taken to reach empirical and theoretical conclusions are outlined wherever possible (Bell et al., 2018; Kuper et al., 2008).

3.4 Ethical Considerations:

Due to the nature of this research, ethical considerations regarding this study were strongly considered. Ethical approval to conduct this research was sought from the University of Canterbury’s Human Ethics Committee (HEC) (Please see Annex B). From this, when reporting data and findings, participants and organisation names were omitted. This enabled respondents to be forthcoming with their responses and provided rich and in-depth answers and viewpoints (Schultze & Avital, 2011), while also allowing for increased integrity and confidentiality of the participants.

Diversity played a key role throughout the study to ensure that this research was inclusive wherever possible. Firstly, between participants in regard to nationality, as well as gender parity between participants was carefully considered. Secondly, diversity between skill levels and industry knowledge factored into participant inclusion. A wide range of levels of experience was included so that fresh perspectives on the topic were heard, as well perspectives from participants with a great deal of industry knowledge.

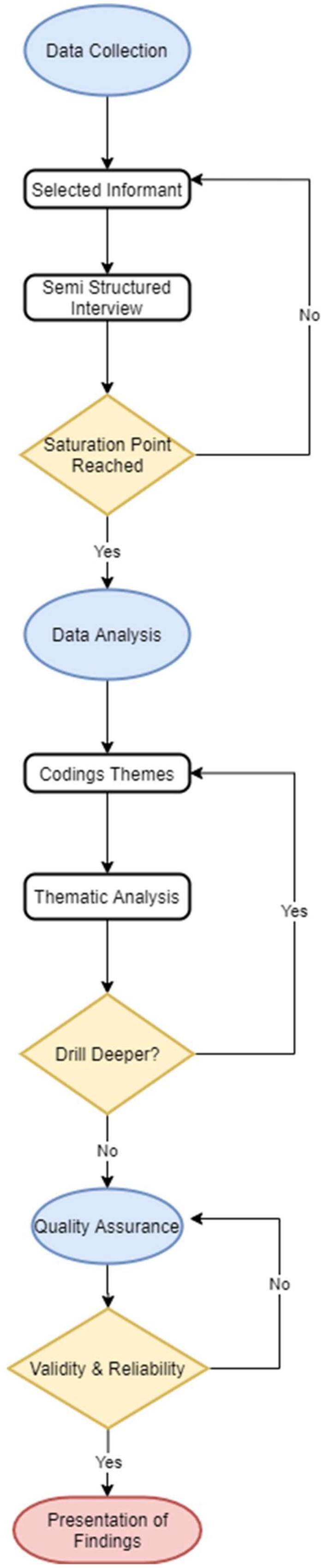
3.5 Validity and Reliability:

This refers to the manner in which interpretive research is assessed for validity and reliability, which is markedly different from built in metrics provided by software tools when using structured equation modelling. Due to this 'Consistency' was a key driver within this study. This relates to the 'trustworthiness' by which the methods have been undertaken, this chapter outlines a 'decision trail' so that our decisions are clear and transparent. Ultimately our processes have been outlined in detail so that an independent researcher should be able replicate the study and derive comparable findings (Noble & Smith, 2015; Walsham, 2006).

Table 5: Research template used to guide the interviews.

Question No.	Research Question
1	What is your understanding of business intelligence and analytics?
2	How does BI&A add value to your organisation?
	To ensure a common understanding of the term, we suggest the following theory-based definition: "Business intelligence and analytics (BI&A) refer to the techniques, technologies, systems, practices, methodologies, and applications that analyse critical business data to help an enterprise better understand it's business and market and make timely business decisions" (Chen et al., 2012, p. 1166).
3	How would you define the success of a BI&A implementation?
4	Which BI&A techniques you do widely use in your organisation?
5	How does BI&A use result in insight generation in your organisation?
6	How do you use BI&A generated insights?
7	What are some key requirements to gather and process data into valuable knowledge?
8	What skills requirements need to be met for BI&A facilitated decisions?
9	What organisational factors influence the value creation process?
10	What are the main problems that you have encountered?
11	Are there any other inhibitors to the value of BI&A?
12	Are there any other comments that you would like to add relating to the value of BI&A?

Figure 8: Flowchart of Research Steps



Chapter Four:

Results and Analysis

This chapter presents the findings from the 14 semi-structured interviews, who provided in-depth answers to the questions outlined in the interview template. This chapter also includes both thematic and word frequency analysis to uncover key themes within the interviews.

4.1 Word Frequency Analysis:

As mentioned above, we utilised NVivo 12 as a semantic tool for both word frequency and thematic analysis to uncover key themes within our data (Bazeley & Jackson, 2013). A word frequency cloud as an effective way to visually represent interview and literature in the form of tags, which are typically single words whose importance is visualised through depicting this through varying sizes and colours based on a word's frequency with the data. Word Frequency Clouds is a useful means to analyse textual data quickly and depicts valuable relationships about significant topics discussed in the course of an interview or secondary data sources (Yi Liu, 2019). It is generated from the original transcripts from the interview as a weighted listed. Due to the voluminous length of these transcripts, it is necessary to extract insights about the most prominent items.

We began this analysis by generating a word frequency cloud of the ten papers that we found that related directly to business analytics and value/value creation. The table below summarises the top 10 papers that comprised the recent research literature which was used from analysis.

Table 6: Top 10 Recent Literature Papers

Author	Title	Publication
Chiang, Grover, Liang, & Zhang, 2018	Strategic Value of Big Data and Business Analytics	Journal of Management Information Systems
Isson & Harriott, 2012	Win with advanced business analytics: Creating business value from your data	John Wiley & Sons
Krishnamoorthi & Mathew, 2015	Business analytics and business value: a case study	Thirty Sixth International Conference on Information Systems
Seddon et al., 2017	How does business analytics contribute to business value?	Information Systems Journal
Someh & Shanks, 2013	The role of synergy in achieving value from business analytics systems	ICIS 2013
Tamm et al., 2013	Pathways to value from business analytics	ICIS 2013
Vidgen, Shaw, & Grant, 2017	Management challenges in creating value from business analytics	European Journal of Operational Research

Wang, Yeoh, Richards, Wong, & Chang, 2019	Harnessing business analytics value through organizational absorptive capacity	Journal of Information and Management
Wixom, Yen, & Relich, 2013	Maximizing Value from Business Analytics	MIS Quarterly Executive
Yoo & Roh, 2018	Value Chain Creation in Business Analytics	Proceedings of the 51st Hawaii International Conference on System Sciences

This then formed the following Word Frequency Cloud (presented below). From this, the most significant intervening words used are Data, Analytics, Business, Value, Information, Organisational and Management.

Below on the left is **Word Frequency Cloud** is presented that highlights significant keywords found in the literature. Next to this on the right is **Word Frequency Cloud** is presented that highlights significant keywords found the interviews that were conducted.

Figure 9: Current Literature Word cloud (Left), Industry Word cloud (Right)

This analysis was then repeated by generating a word frequency cloud of the interview transcripts, which then formed the following Word Frequency Cloud (presented below). From this, the most significant intervening words used are: Think, Business, Actually, People and Analytics. Stemming from this the world frequency cloud in conjunction with the one above to form our key nodes and track the interview transcripts in order to perform an accurate analysis which is often the goal when performed qualitative thematic analysis (Bazeley & Jackson, 2013).

Table 7: Most Frequent Words Used, Literature vs Industry:

Most Frequent (*Current Literature*)	Most Frequent (Industry)
Data	Business
Business	Think
Analytics	Actually
Value	People
Information	Analytics

Table 8: Least Frequent Words Used, Literature vs Industry:

Least Frequent (*Current Literature*)	Least Frequent (Industry)
Assets	Pretty
User	Build
Resource	Analyst
International	Sense
Culture	Point

4.1 Thematic Analysis:

As previously mentioned, all 14 practitioner interviews for this thesis were recorded and then later transcriber verbatim. In order to aid with answering the research question, thematic analysis was chosen to analyse the collected data in a structured and systematic manner (Bazeley & Jackson, 2013; Bell et al., 2018). Thematic Analysis can either be theory-driven or data-driven, where the analysis either starts with theory derived from the literature or raw data/ interview transcripts (Braun & Clarke, 2006). This study employed both approaches, using mainly a theory-driven approach was utilized at the beginning, where indications in the findings were structured around the research model. This was followed by a more empirical approach, exploring the raw data to identify new trends and indications within the contexts not identified by prior literature (Bazeley & Jackson, 2013).

4.1.2 Thematic Categories:

The themes discovered during our analysis were subsequently split into two categories outlined below (Braun et al., 2019; Fereday & Muir-Cochrane, 2006).

Primary theme: A primary theme was categorised as a theme within the data which was bold and distinct. This was given to themes which resonated between many participant responses or academics.

Secondary theme: A secondary theme was not as prevalent in the data set; however, the theme was still corroborated by another participant or academic, therefore was notable.

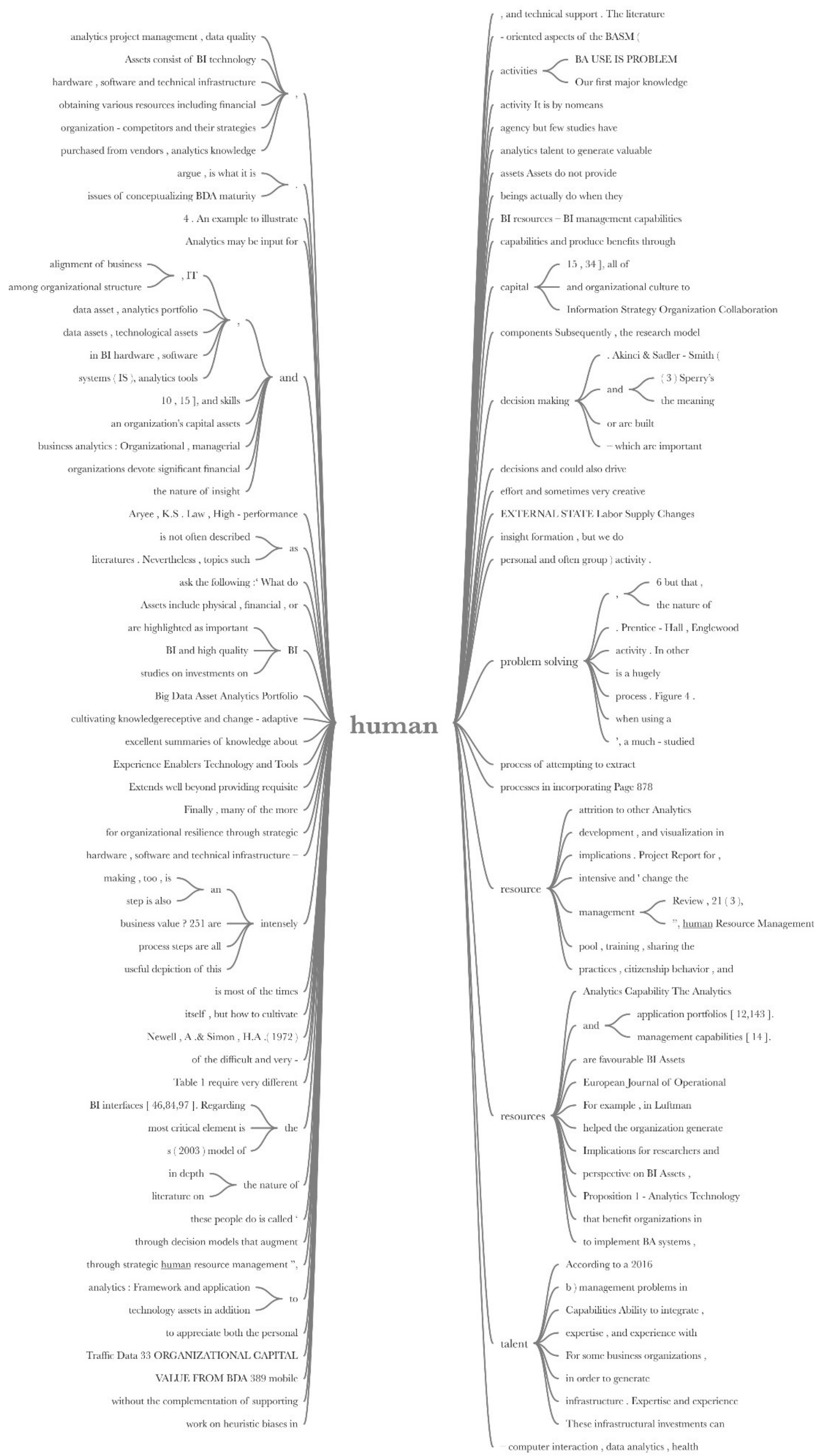
4.2 Thematic Analysis of Literature:

We began thematic analysis on the first value driver '*Data Assets'*. (Grover et al., 2018) establishes this value driver through noting that "BA initiatives without clear business goals and strategies will fail"(Grover et al., 2018, p. 403). Through examining the literature surrounding this, (Chae, 2014; Conboy et al., 2018; Enders, 2018; Grover et al., 2018; Llave et al., 2018; Tamm et al., 2013; Wang et al., 2015; Wixom et al., 2013; Ylijoki & Porras, 2018) point towards an organisational need for well-governed data in order to deliver value for their BA operation. With Conboy et al. (2018, p. 3) stating that "Data governance is essential to maximising value from business analytics". Moving from this thematic analysis uncovered the primary theme of High-quality BI Technology to fit organisations task and data strategy (Cosic et al., 2012; Duan et al., 2018; Seddon et al., 2017; Shanks et al., 2010; Tamm et al., 2013; Teo et al., 2016; Wang et al., 2019; Wixom et al., 2013; Yoo & Roh, 2018) with Wang et al. (2019, p. 3) stating "BA tools unleash the full potential of BA technologies in helping organization achieve competitive advantage." and Yoo and Roh (2018, p. 874) suggesting it as a "monumental driver of value creation in BA". The first secondary theme that was uncovered from the literature was Cloud-based data assets which are scalable services based on demand (Cao & Duan, 2017; Chen et al., 2012; Grover et al., 2018; Llave et al., 2018; Rehman et al., 2016). With an additional secondary theme supporting the value of continuous hardware improvement and investments also being prevalent in the literature (Davern & Kauffman, 2000; Dehning et al., 2003; Soh & Markus, 1995; Teo et al., 2016; Trieu, 2017)

Next, thematic analysis began on the second value driver '*Human Capabilities*' which presented significant themes within the analysis. From this, a strong primary theme was identified around the need for trained analytical staff in order to deliver value. (Božič & Dimovski, 2019; Buldoo, 2018; Côrte-Real, Ruivo, & Oliveira, 2019; Lamba & Dubey, 2015; Ransbotham et al., 2016; Tamm et al., 2013; Wang & Byrd, 2017; Wang et al., 2015; Ylijoki & Porras, 2018) With Božič and Dimovski (2019, p. 99) noting that "…data and analytical skills necessary to exploit the technology fully" and Ylijoki and Porras (2018, p. 9) stating that "Analytical skills and capabilities turn information into knowledge". The next primary theme which was under covered within the literature surrounded the need for a high level of business knowledge and business functions (Akter et al., 2016; Božič & Dimovski, 2019; Burton-Jones & Grange, 2012; Chen et al., 2012; Elbashir et al., 2008; Gao et al., 2017; Lund Vinding, 2006; Mangematin & Nesta, 1999; Soh & Markus, 1995; Wang et al., 2019; Wixom et al., 2013). With Božič and Dimovski (2019, p. 96) pointing out that "…employees with strong business knowledge and technical skills are more efficient in recognizing and valuing new external knowledge, therefore, increasing the knowledge level in the firm". A secondary theme which appeared within this value driver was the need for deep domain knowledge (Akter et al., 2016; Chen et al., 2012; Krishnamoorthi & Mathew, 2015; Nevo & Wade, 2010; Trieu, 2017; Wang et al., 2019) with Vidgen et al. (2017) stating that "The business analytics function will need to build deep understanding of the organization and its business domain if it is to create lasting value".

Figure 10: Example of NVivo Thematic Analysis

Semantic Network Diagram for label = Human



Thematic Analysis then began on the '*BA Impacts'* value driver. From this analysis, the first primary theme uncovered surrounded Timely and Decisive use of BA generated insights in order to create value (Caya & Bourdon, 2016; Grytz & Krohn-Grimberghe, 2018; Ramamurthy et al., 2008; Wang & Byrd, 2017; Wang et al., 2015; Yoo & Roh, 2018). With value being generated by using "Business Analytics to drive efficiency in strategic and day-to-day decision making Krishnamoorthi and Mathew (2015, p. 2). In conjunction with this, a secondary primary theme was also uncovered around improved organisational performance, with BA impacts driving value through improved organisational performance (Božič & Dimovski, 2019; Caya & Bourdon, 2016; Côrte-Real, Ruivo, & Oliveira, 2019; Elbashir et al., 2008; Grover et al., 2018; Kapoor & Kabra, 2014; Sharma et al., 2017; Trieu, 2017; Ylijoki & Porras, 2018). In conjunction to this, a secondary theme was also uncovered which was were BA contributed to value through enabling a competitive position (Cao & Duan, 2017; Dehning et al., 2003; Llave et al., 2018; Moreno et al., 2019; Trieu, 2017).

Our analysis then moved on themes surrounding '*Business Analytics Operations'*. Key themes appeared around this value driver for the first theme surrounding this was the need for Consumer-Driven Analytics Strategy (Akter et al., 2016; Ashrafi et al., 2019; Chen et al., 2012; Chiang et al., 2018; Dong & Yang, 2018; Grover et al., 2018; Lim et al., 2013; Llave et al., 2018; Van Rijmenam et al., 2018; Vidgen et al., 2017) as stated by Llave et al. (2018, p. 7) "consumer insight can help enterprises to focus on the right customers, identify customers with high churn probability" and Enders (2018, p. 4) stating that "value-exchange process is based on the needs of the consumers". The second primary theme identified in the extant literature supported the need for responsive, agile practices to be present within the organisation to aid value creation (Ashrafi et al., 2019; Conboy et al., 2018; Llave et al., 2018; Ramanathan et al., 2017; Sharma et al., 2007; Stevens, 2017; Tamm et al., 2013; Van Rijmenam et al., 2018; Vidgen et al., 2017; Wixom et al., 2013; Ylijoki & Porras, 2018). Two secondary themes were also present during the analysis, the first that appeared was the use of multidisciplinary teams in BA use (Božič & Dimovski, 2019; Capellá et al., 2012; Côrte-Real, Ruivo, Oliveira, et al., 2019; Delen & Zolbanin, 2018; Duan et al., 2018). With Božič and Dimovski (2019, p. 99) stating that "Ideally, these firms need multidisciplinary data scientists that own a combination of data, analytics and business knowledge which would allow them to communicate with, and understand, the broader business environment". The second primary theme which appeared pointed towards the use of an Innovative workflow (Ashrafi et al., 2019; Cosic et al., 2012; Dehning et al., 2003; Elbashir et al., 2008; Shanks et al., 2010; Stevens, 2017; Wixom et al., 2013). With Cosic et al. (2012, p. 7) stating organisations should "use BA technologies to develop innovative and more effective processes and products that result in better organisational performance and create competitive advantage. It frequently involves risk-taking and is enhanced through learning that results from experience, trial and error and experimentation".

Lastly, thematic analysis was undertaken on the '*Organisational Factors'* value driver. The top primary theme that was identified surrounded the need for an analytic and evidence-based making culture within the organisation (Buldoo, 2018; Chen et al., 2012; Duan et al., 2018; Grytz & Krohn-Grimberghe, 2018; Holsapple et al., 2014; Kapoor & Kabra, 2014; Krishnamoorthi & Mathew, 2015; Lamba & Dubey, 2015; LaValle et al., 2011; Stevens, 2017; Vidgen et al., 2017). Lamba and Dubey (2015, p. 1) referenced a survey conducted by MIT Centre for Digital Business and McKinsey's business technology office reveals that data-driven organizations are 5% more productive and 6% more profitable than their competitors. The next primary theme identified supported continued investments in BA initiatives within organisations (Côrte-Real, Ruivo, Oliveira, et al., 2019; Corte Real et al., 2014; Cosic et al., 2012; Davern & Kauffman, 2000; Kiron & Shockley, 2011; Seddon et al., 2017; Tamm et al., 2013; Wang et al., 2019; Wang & Byrd, 2017; Wang et al., 2015; Wixom et al., 2013; Ylijoki & Porras, 2018; Yoo & Roh, 2018). With Tamm et al. (2013, p. 7) noting that "A key point here is that a large investment in BI-platform infrastructure, data extraction, and data quality is needed to enable such routine BA use to be easy and secure for end-users". The third primary theme that was uncovered surrounds continual Executive commitment and championship towards BA within the organisation (Božič & Dimovski, 2019; Grover et al., 2018; Kiron & Shockley, 2011; LaValle et al., 2011; Ramakrishnan et al., 2012; Ramamurthy et al., 2008; Seddon et al., 2017; Sharma et al., 2007; Tamm et al., 2013; Vidgen et al., 2017; Wang et al., 2019; Wixom et al., 2013). Grover et al. (2018, p. 419) states that "Successful initiatives are usually championed through an integrative BDA strategy and strong leadership". A secondary theme surrounding the alignment of BA capability with business strategy was also uncovered (Akter et al., 2016; Côrte-Real, Ruivo, & Oliveira, 2019; Côrte-Real, Ruivo, Oliveira, et al., 2019; Cosic et al., 2012; Grover et al., 2018; Moreno et al., 2019) with Cosic et al. (2012, p. 5) defining this as "The alignment of an organisation's BA initiatives with its business strategy".

Table 9: Tabulation of thematic results from literature.

Value Driver	Primary Theme	Secondary Theme
Definition	Sounder, more evidence-based business decisions	
Data Assets	Well Governed Data and Strategy, High-quality BI/A Technology to fit organisations task and data strategy	Cloud-Based – Scalable Service, Continuous Hardware Improvement
Human Capabilities	Analytical, High levels of business knowledge and skills	Deep Domain Knowledge
BA Impacts	Timely and Decisive use, Improved organisational performance	Competitive position
BA Operations	Consumer-Driven Analytics Strategy, Data-Driven Organisation, Responsive Agile Practices	Multidisciplinary Teams, Innovative workflow,
Organisational Factors	Analytic and evidence-based making culture, Continued investment in BA initiatives, Executive commitment/championship	Alignment of BA capability with business strategy

4.3 Thematic Analysis of Research Participants:

We began our thematic analysis by analysing question 3 that was asked during the interviews where we read out the following definition derived from literature and then asked the participants to define their own success of a BI&A implementation.

> *Definition derived from literature: "Business intelligence and analytics (BI&A) refers to the techniques, technologies, systems, practices, methodologies, and applications that analyse critical business data to help an enterprise better understand it's business and market and make timely business decisions" (Chen et al., 2012, p. 1166).*

From which we found that participants mostly provided a definition matching the one provided by literature, however, there were some new themes identified. The first most significant theme that was identified as missing from the definition provided by (Chen et al., 2012) was the 'People' / 'Capabilities' aspect and was noted by a large proportion of the participants.

Following this thematic analysis then began on the first value driver '*Data Assets'*. Strong themes presented within this data with the most prominent being Data Integrity which has mentioned in the majority of interviews. Other primary themes were apparent where the need for robust Data Governance and Raw Granular Data. Secondary themes where apparent where Well Documented systems and processes as well as Cloud-based analytics.

Next, thematic analysis began on the second value driver '*Human Capabilities'* which presented significant themes within the analysis. From this, we found a Full Business Understanding to be a prominent theme throughout the analysis with a need for Data Literacy, also being a primary theme in the data set. Secondary themes which also appeared included Strong People and Negation Skills, a need for Experimental Nature, Critical Thinking and being also to convey a Strong Data Story.

Thematic Analysis then began on the '*BA Impact*s' value driver. From this Defining the Scope of a Solution, Analysis resulting in an Outcome and Timely Decisions were found to be primary themes which linked to this driver. A secondary theme which was also found was that Businesses and Organisational Agility surrounding analytics.

Our analysis then moved on themes surrounding '*Business Analytics Operations'*. Key themes appeared around this value driver, with primary themes being Prioritisation Method surround BA task within the business to ensure that the most valuable work is being complete foremost. A second primary theme surrounding an Agile approach within Business Analytics, allowed organisations to respond quicker to insight. Secondary themes which also appeared include Multidisciplinary Teams and Self-service analytics and reports that can be tailored an employee's needs.

Lastly, thematic analysis was undertaken on the '*Organisational Factors'* value driver. The top primary theme that was identified was Executive Sponsorship supporting and progressing Business Analytics use within the organisation. Other primary themes included the need for organisations to invest in infrastructure supporting analytics use within the business and also the requirement to have a clear guiding data-driven strategy in place for the direction of analytics within the organisation. Secondary themes which also appeared include having in place a risk-taking a supportive culture surrounding analytics use.

Table 10: Tabulation of thematic results of practitioner interviews.

Value Driver	Primary Theme	Secondary Theme
Definition	People	Cusp of Technology and Business
Data Assets	Data Integrity, Strong Data Governance, Raw Granular Data	Well Documented, Cloud-Based, Continuous Improvement
Human Capabilities	Full Business Understanding, Data Literacy	Influential People and Negation Skills, Experimental Nature, Critical Thinking, Strong Data Story
BA Impacts	Defining the Scope of Solution, Result in an Outcome, Timely Decisions	Business Agility
BA Operations	Prioritisation Methods, Agile Approach	Multidisciplinary Teams, Self-service analytics and reports / Personalisation
Organisational Factors	Executive Sponsorship, Investment in BA and Clear Data-Driven Strategy	Risk-Taking

4.4 Value Driver Corroboration and Gap Analysis:

Following the analysis above, we then looked to see what corroborations and gaps occurred both in practice and in the extant literature. This process was essential to undertake as it highlighted possible areas for further research to be undertaken, particular surrounding a possible disconnect between the academics and professionals in this domain. The findings from this section will be elaborated further in the Discussion section; however, a summary of the results is displayed in tabular form below, alongside a brief synopsis of the results.

The gap analysis aimed to highlight key differences between findings in resent literature and practice. This was conducted in order to evaluate the limitations of the current business analytics landscape and identify gaps which need to be filled. We considered the viewpoints of different players within the business analytic ecosystem, with this analysis highlighting the most critical gaps for the development of future BA frameworks and use (Jennings, 2000; Kuper et al., 2008; Mineraud et al., 2016).

Firstly, a comparison was made between the definition of Business intelligence and analytics from (Chen et al., 2012) and the definition provided by the respondents during the interview. From these respondents largely corroborated the (Chen et al.) definition; however, the majority of respondents raised that “People” should be included in the definition, as shown below.

Table 11: Summary of these results from the analysis of the definition.

BA Definition	Corroborations	Theoretical Gaps	Practice Gaps
“Business intelligence and analytics (BI&A) refers to the techniques, technologies, systems, practices, methodologies, and applications that analyse critical business data to help an enterprise better understand it's business and market and make timely business decisions” (Chen et al., 2012, p. 1166).	Sounder, more evidence-based business decisions		People

The comparison between the two bodies of knowledge was subsequently made on the 5 Business Analytics value drivers. The first value driver which was analysed was ‘*Data Assets’*, which relates to analytical tools and software packages which enable BA use, this also encompasses backend infrastructure such as data storage and processing. Comparing between the responses provided by the professionals interviewed and the extant literature, corroborations included the need for well-governed data, data integrity, the use of cloud-based services which are scalable in nature and continuous hardware improvement to data assets within the organisation. A theoretical gap present was the need for high-quality BI/A technology to fit an organisations needs and data strategy, rather than an off the shelf product which may not be best suited for the organisation’s needs. Practice gaps which were not present in the literature included the need for raw granular data and the need for business analytics systems and processes to be well documented within organisations.

Comparing the second driver ‘*Human Capabilities’*, which includes analytical training and human resources supporting insight and decision making within the organisation. Corroborations for this value driver existed, surrounding the need for deep domain knowledge to be present within analytical professionals. A theoretical gap which was present placed high importance on academic analytical training. A practice gap which existed supported the need for influential people and negation skills, an experimental nature, critical thinking and the skills to need a strong and convincing story with the data.

Analysis next moved onto the third value driver ‘*BA Impacts’* which is based around the output of BA use, so of which can include Improved performance, operations efficiency, targeted products, process alignment and expansion in a new market. The main corroboration for this value driver surrounded the need for Timely decisions and actions to be made from BA generated insights. A theoretical gap around the need for the organisation to be placed in a competitive position within industry was present. In conjunction practice gaps which existed included the need for business agility and the ability to react quickly to a changing climate, as well as the need for to define the scope and scale of a BA solution.

The fourth value driver which was analysed for corroborations and gaps was '*BA operations*', which entails Business Analytics processes, work practices and routines performed within the organisation to support BA use. Corroborations between theory and practice for this value driver supported the need for a data-driven organisation present, the benefits of working in multidisciplinary BA teams and the use of agile project workflows. The theory calls for Innovative workflows to be present within the organisation, which can aid BA impact. Practice gaps which were not displayed in theory include the use of making available self-service analytics and reports to employees within the organisation, with the options to enable personalisation to an employee needs.

Lastly, the '*Organisational Factors*' value driver was analysed. This value driver incorporates organisational size, scope and absorptive capacity as well as strategic factors to assist with the successful adoption and use of BA. Corroborations for this value driver include the need for strong executive sponsorship behind BA use within the organisation, as well as continued investment in BA operations and assets. A theoretical gap existed around the need to align BA capability with the strategy and direction of the business. In addition, a practice gap which didn't occur in theory surrounded the need for the organisation to be risk-taking in its use of BA.

Table 12: Corroborations and Gaps between Research and Practice

Value Driver	Literature	Corroborations	Theoretical Gaps	Practice Gaps
Data Assets	Analytics tools and packages from vendors such as IBM and SAP, hardware and infrastructure	Well Governed Data, Data Integrity, Cloud-Based – Scalable services, Continuous Hardware Improvement	High-quality BA/I Technology to fit organisations task and data strategy	Raw Granular Data, Well Documented
Human Capabilities	Analytical training and skills to decode output into insight and decision making	Deep Domain Knowledge	Analytical Training	Influential People and Negation Skills, Experimental Nature, Critical Thinking, Strong Data Story
BA Impacts	Improved performance, operations efficiency, targeted products, process alignment and expansion in new markets	Timely Decisions and actions	Competitive Position	Business Agility, Defining the Scope of Solution
BA Operations	Business Analytics processes, work practices and routines performed within the organisation to support BA use	Data-Driven Organisation, Multidisciplinary Teams, Agile Workflow	Innovative workflow	Self-service analytics and reports / Personalisation
Organisational Factors	Organisational size, scope and absorptive capacity as well as strategic factors to assist with the successful adoption and use of BA.	Executive Sponsorship, Continued Investment in BA within the Organisation	Alignment of BA capability with business strategy	Risk-Taking

4.6 Value Inhibitors

Our research also asked participants what inhibits business analytic value generation as an attempt to improve its implementation and application in the future. The responses from our participants were subsequently thematically analysed and categorised into their relating value inhibitor. (Note that these value inhibitors share the same factors as above so that analysis could be completed.)

Thematic analysis on the first value inhibitor '*Data Assets'* uncovered several primary themes within the dataset. The first of these themes surrounded Siloed Systems being present within organisations, leading to possible fracturing and duplication of data sources inhibiting BA use. The next theme identified surrounded the incorporation of Legacy systems into a BA pipeline, which introduces throughput and compatibility challenges. The last primary theme uncovered placed significant importance on data quality, with this having a flow-through effect as to the accuracy of insights generated. Two secondary themes were also established through our analysis of the responses. The first spanning the growing amounts of tech debt generated through BA use due to the rapid evolution of the industry. The second theme highlighted the significant fracturing of technology and tools, which is now existent in the industry, with organisations now having to adopt a growing range of analytical tools from vendors.

The next value inhibitor analysed '*Human Capabilities'*, displayed a primary theme around the current shortage of skilled analytical staff possessing the experience and qualities that the industry currently requires. Two secondary themes were also present, which relate to the primary theme. The first which was uncovered surrounded staff retention and the struggle some organisations are facing in retaining their quality staff due to the competitiveness of the industry. In conjunction, the second theme identified relates to a disconnect of the current remuneration some organisations are budgeted to pay, compared to the remuneration skilled analysts can command in the market.

The third value inhibitor analysed was '*BA Impacts'*. This inhibitor presented two primary themes; the first emphasised the importance of being accurate when presenting results and avoid distorting or enlarging the results, with participants noting that if not followed this can impact trust in data. The second primary theme surrounded the difficulty in measuring value derived from BA insights in monetary terms. A secondary theme was also present surrounding the requirement of meaningful reporting were organisations should focus on reporting that is meaningful and will result in value, rather than mundane reporting, which does not result in value.

Following this numerous primary themes were uncovered within the '*BA Operations'* value inhibitor. The first theme present supported the ideology of focusing on value delivery, where organisations should focus on BA tasks which will derive immediate value. The second theme emphasised the fiscal and budgeting challenges that BA departments and teams currently face within organisations, which has the ability to inhibit insight generation from occurring. The third theme present placed importance on the documentation and knowledge management of BA system enhancements so that these are safeguarded in detail in the event that a staff member departs from the organisation. Two secondary themes were also present after our analysis; the first surrounded the growing saturation of BA vendors and tools available for organisations to select from, with organisations having a challenging time selecting technology that is best fit for their own use. The second theme present involved the need for a collaborative workflow to be present within the organisation, with it being beneficial for BA departments and teams to involve other parts of the business in their work.

The last value inhibitor '*Organisational Factors'* displayed a primary theme present revolving around the importance for a company to place and build up trust in its data. Respondents noted that this could take up a long time to build up within the organisation; however, this can be quickly lost if integrity is compromised. A secondary theme which supported an organisation with a culture supporting data-driven decisions was also present; otherwise, BA insights risk not being acted upon.

Table 13: Tabulation of Value Inhibitors and Themes.

Value Inhibitor	Primary Theme	Secondary Theme
Data Assets	Siloed Systems, Legacy Systems, Data Quality	Tech Debt, Fracturing of Technology
Human Capabilities	Skilled Analytical Staff to fit industries needs	Staff Retention and Remuneration
BA Impacts	Accurate not distorted Presentation, Measuring Value	Meaningful Reporting
BA Operations	Focus on Value Delivery, Budget and Investment in BA, Well Documented system enhancements	Vendor Saturation and Tool selection, Non -Collaborative Workflow
Organisational Factors	Company trust in Data	Culture surrounding data-driven decisions

Chapter Five:

Findings and Discussion:

In this chapter, the analysis of the qualitative findings in conjunction with the theoretical background is presented. As this study investigates, how does Business Analytics contribute to business value within organisations the analysis and discussion are centred around a wider-reaching lens. Further, this chapter concludes by summarising the findings, meanwhile also providing an extended discussion regarding the qualitative findings and what implications they have in terms of research.

5.1 Practice Definition of Business Analytics

As stated earlier, “Business intelligence and analytics (BI&A) refer to the techniques, technologies, systems, practices, methodologies, and applications that analyse critical business data to help an enterprise better understand it's business and market and make timely business decisions” (Chen et al., 2012, p. 1166). Based on our analysis, ‘People’ in the business analytic context play a significant role in the success and value creation in a business analytics system, however absent from the definition provided by (Chen et al., 2012). The extant definition provided neglects the human resourcing portion of a BA implementation, which quite notably the respondents pointed out that the ‘People’ aspect act as a keystone supporting every part of a BA pipeline. A value inhibitor for this definition surrounded a ‘culture of distrust’ in data existed within organisations, were ‘gut feel’ was acted on, rather than data generated insights and decisions.

5.2 Data Assets

The *Data Assets* value driver which relates to analytical tools and software packages which enable BA use, this also encompasses backend infrastructure such as data storage and processing (Grover et al., 2018). The findings show that corroborations between research and practice exist, corroborations included the need for ‘well-governed data’, ‘data integrity’, the use of ‘cloud-based services’ which are scalable in nature and continuous hardware improvement to data assets within the organisation. Highlighting the extant literature surrounding this, (Chae, 2014; Conboy et al., 2018; Enders, 2018; Grover et al., 2018; Llave et al., 2018; Sharma et al., 1991; Tamm et al., 2013; Wang et al., 2015; Wixom et al., 2013; Ylijoki & Porras, 2018) point towards an organisational need for ‘well-governed data’ in order to deliver value for their BA operation. With Conboy et al. (2018, p. 3) stating that “Data governance is essential to maximising value from business analytics”. In addition, the literature supported the use of ‘Cloud-based data’ assets which are scalable services based on demand (Cao & Duan, 2017; Chen et al., 2012; Grover et al., 2018; Llave et al., 2018; Rehman et al., 2016).

However, a notable theoretical gap is present regarding the need for ‘high-quality BI/A technology’ to fit an organisations needs and data strategy, rather than an off the shelf product which may not be best suited for the organisation’s needs.

Practice gaps which were not present in the literature included the need for ‘raw granular data’ and the need for business analytics systems and processes to be ‘well documented’ within organisations.

Potential value inhibitors for *Data Assets* include ‘siloed systems’ being present within organisations, leading to possible fracturing and duplication of data sources/ islands of automation which do not interoperate, inhibiting BA use. The incorporation of ‘legacy systems’ into a BA pipeline, which introduces throughput and compatibility challenges, and data quality, with this having a flow-through effect as to the accuracy of insights generated. Secondary themes also included the spanning the growing amounts of ‘tech debt’ generated through BA use due to the rapid evolution of the industry, and the extensive ‘fracturing of technology’ and tools which is now existent in the industry, with organisations now having to adopt a growing range of analytical tools from vendors.

5.3 Human Capabilities

Next, we examine the *Human Capabilities* value driver, this refers to employees and contractors that are trained to work with analytics and skilled to decode output are highlighted as critical assets that enable organisations to realise business value (Božič & Dimovski, 2019; Culumber, 2017; Lamba & Dubey, 2015; Leon et al., 2018; Sharma et al., 2007; Stevens, 2017; Wang et al., 2019). Many studies have suggested that an organisation's human resources are a vital driver for BA success (Côrte-Real, Ruivo, Oliveira, et al., 2019; Grevler, 2017; Holsapple et al., 2014; Seddon et al., 2017; Tamm et al., 2013; Trkman et al., 2010; Wang et al., 2019). The findings support what previous research has identified within this value driver; however, on the contrary, several new factors were found. Corroborations for this value driver existed, surrounding the need for ‘deep domain knowledge’ to be present within analytical professionals. Which is highlighted by previous research by surrounding the need for a high level of ‘business knowledge’ and business functions is critical (Akter et al., 2016; Božič & Dimovski, 2019; Burton-Jones & Grange, 2012; Chen et al., 2012; Elbashir et al., 2008; Gao et al., 2017; Lund Vinding, 2006; Mangematin & Nesta, 1999; Soh & Markus, 1995; Wang et al., 2019; Wixom et al., 2013). With Božič and Dimovski (2019, p. 96) pointing out that “…employees with strong business knowledge and technical skills are more efficient in recognizing and valuing new external knowledge, therefore, increasing the knowledge level in the firm”. In conjunction Vidgen et al. (2017) stating that “The business analytics function will need to build a deep understanding of the organization and its business domain if it is to create lasting value”.

A theoretical gap which was present placed high importance on ‘academic analytical training’ with the need for trained analytical staff in order to deliver value supported in research (Božič & Dimovski, 2019;

Buldoo, 2018; Côrte-Real, Ruivo, & Oliveira, 2019; Lamba & Dubey, 2015; Ransbotham et al., 2016; Tamm et al., 2013; Wang & Byrd, 2017; Wang et al., 2015; Ylijoki & Porras, 2018). With Božič and Dimovski (2019, p. 99) noting that "…data and analytical skills necessary to exploit the technology fully" and Ylijoki and Porras (2018, p. 9) stating that "Analytical skills and capabilities turn information into knowledge". As highlighted by the literature, this is a crucial component aiding value delivery within organisations.

Our analysis exposed a practice gap pertaining to the need for 'influential people' and 'negotiation skills', an 'experimental nature', 'critical thinking' and the skills to produce a 'strong and convincing story' with the data. This gap highlights a potential disconnect placed on the importance of hard skills (academic analytical training) and soft skills (e.g. People and negation skills) should be explored in future research on the subject. Because of this, organisations are encouraged to combine analytical talents with other skills of employees in the pursuit of greater business results. (Leon et al., 2018; Trieu, 2017). "Again, it is important to point out that insight occurs in people's heads, not in computers..." Seddon et al (2017, p. 249) and Božič and Dimovski (2019, p. 96) adding that "…employees with strong business knowledge and technical skills are more efficient in recognizing and valuing new external knowledge, therefore, increasing the knowledge level in the firm". In summary of the literature, there is a suggestion that a strong focus in high-quality BA assets, with an emphasis on human resources, is overall favourable towards BA business value.

Potential value inhibitors that were analysed for *Human Capabilities* included a primary theme around the current shortage of 'skilled analytical staff' possessing the experience and qualities that the industry currently requires. Two secondary themes were also present, which relate to the primary theme. The first which was uncovered surrounded 'staff retention' and the struggle some organisations are facing in retaining their quality staff due to the competitiveness of the industry. In conjunction, the second theme identified relates to a disconnect of the current 'remuneration' some organisations are budgeted to pay, compared to the remuneration skilled analysts can command in the market. In summary, this highlights a lag between what organisations are budgeted to pay versus what prospective employees expect in terms of remuneration, which can also lead to the other inhibiting factors identified.

To synthesise the findings, the *Capabilities* value driver helps organisations realise value through insight generation which occurs through analytical staff (Seddon et al., 2017), without high calibre employees in a business analytics implementation organisations can potentially put at risk value generation.

5.4 Business Analytics Impacts

The *BA Impacts* value driver refers to the output of BA use, so of which can include improved performance, operations efficiency, targeted products, process alignment and expansion into new markets. The main corroboration for this value driver surrounds the need for 'timely decisions and actions' to be made from BA generated insights. From this analysis, the first primary theme uncovered surrounded 'timely and decisive' use of BA generated insights in order to create value (Caya & Bourdon, 2016; Grytz & Krohn-Grimberghe, 2018; Ramamurthy et al., 2008; Wang & Byrd, 2017; Wang et al., 2015; Yoo & Roh, 2018). With value being generated through using "Business Analytics to drive efficiency in strategic and day-to-day decision making Krishnamoorthi and Mathew (2015, p. 2). 'Timely decision' making was found to provide an organisation with the ability to fully exploit possibly underutilised parts of the business through acting on insights derived from organisational data and analysis, however 'timeliness' is a vital aspect of this as insight derived must be current.

A theoretical gap around the need for the organisation to be placed in a 'competitive position' within industry was present (Cao & Duan, 2017; Dehning et al., 2003; Llave et al., 2018; Moreno et al., 2019; Trieu, 2017). Moreover, we can assume from this research that a 'competitive position' within an organisations industry dramatically impacts the effectiveness and magnitude of business analytics impacts.

Next, practice gaps which existed included the need for 'business agility 'and the ability to react quickly to a changing climate, as well as the need for to 'define the scope and scale of a BA solution'. The participants within the research highlighted the need to be able to quickly adapt to changing markets through 'business agility', whether this is caused through market disruption, supply chain factors or more widespread market shifts. 'Defining the scope of a solution' was also highlighted as a critical factor due to business analytical solutions often being susceptible to snowballing in scope; hence a clearly defined stopping point is crucial. Thus, providing added opportunities for further research to be undertaken to explore this gap in extant literature.

Value inhibitors found for this driver included two primary themes, the first emphasised the importance of 'accuracy' when presenting results and avoid distorting or enlarging the results, with participants noting that if not followed this can impact trust in data. The second primary theme surrounded the difficulty in 'measuring value' derived from BA insights in monetary terms. A secondary theme was also present surrounding the requirement of meaningful reporting were organisations should focus on reporting that is meaningful and will result in value, rather than mundane reporting, which does not result in value. In summary, these inhibitors suggest that when reporting, results should not be 'cherry-picked', instead they should be reported at face value so that integrity and trust in data is retained. In conjunction, fiscal benefits directly resulting from a BA initiative or insight should be measured on an organisational wide level, as benefits are often realised in departments throughout the organisation

To synthesise *Business Analytic Impacts* generates value through efficiency gains, in strategic and day to day decision making. However, organisations should be aware of possible inhibitors to this, such as ‘distorting results’ in order for value generation to be maximised.

5.5 Business Analytics Operations

As stated earlier, the *Business analytics Operations* value driver concerns Business Analytics processes, work practices and routines performed within the organisation to support BA use. The findings present corroborations between theory and practice for this value driver supported the need for a ‘data-driven organisation’ present (Akter et al., 2016; Ashrafi et al., 2019; Chen et al., 2012; Chiang et al., 2018; Dong & Yang, 2018; Grover et al., 2018; Lim et al., 2013; Llave et al., 2018; Van Rijmenam et al., 2018; Vidgen et al., 2017) as stated by Llave et al. (2018, p. 7) “consumer insight can help enterprises to focus on the right customers, identify customers with high churn probability” and Enders, (2018, p. 4) stating that “value-exchange process is based on the needs of the consumers”. The other corroboration identified surrounded the benefits of working in ‘multidisciplinary BA teams’ and the use of ‘agile’ project workflows. (Božič & Dimovski, 2019; Capellá et al., 2012; Côrte-Real, Ruivo, Oliveira, et al., 2019; Delen & Zolbanin, 2018; Duan et al., 2018). With Božič and Dimovski (2019, p. 99) stating that “Ideally, these firms need multidisciplinary data scientists that own a combination of data, analytics and business knowledge which would allow them to communicate with, and understand, the broader business environment” The last corroboration identified surrounded the need for responsive, ‘agile’ practices to be present within the organisation to aid value creation as well as to respond quicker to insight (Ashrafi et al., 2019; Conboy et al., 2018; Llave et al., 2018; Ramanathan et al., 2017; Sharma et al., 2007; Stevens, 2017; Tamm et al., 2013; Van Rijmenam et al., 2018; Vidgen et al., 2017; Wixom et al., 2013; Ylijoki & Porras, 2018). Two secondary themes were also present during the analysis; the first that appeared was the use of ‘multidisciplinary teams’ in BA use.

The theory calls for Innovative workflows to be present within the organisation, which can aid *BA Impact*. (Ashrafi et al., 2019; Cosic et al., 2012; Dehning et al., 2003; Elbashir et al., 2008; Shanks et al., 2010; Stevens, 2017; Wixom et al., 2013). With Cosic et al. (2012, p. 7) stating organisations should “use BA technologies to develop innovative and more effective processes and products that result in better organisational performance and create competitive advantage. It frequently involves ‘risk-taking’ and is enhanced through learning that results from experience, trial and error and experimentation”.

Practice gaps which were present within theory include the use of making available ‘self-service’ analytics and reports to employees within the organisation, with the options to enable personalisation to employee needs e.g. personalizes dashboards and cockpits. Participants within the study noted this as a critical tool to help mitigate workload pressure on their department, through providing employees with the means to run their own queries and manipulate data in an ad hoc basis and utilise this for fundamental analysis that is needed within the organisation.

However, regarding the inhibiting aspect of this value driver, the following themes were uncovered within the *BA Operations*. The first theme present supported the ideology of focusing on 'value delivery', where organisations should focus on BA tasks which will derive immediate value. Where the analytics departments with organisations should focus on tasks which will deliver the most impact, rather than trivial reports which do not deliver the same level of value. The second theme emphasised the fiscal and 'budgeting challenges' that BA departments and teams currently faced within organisations, which can inhibit insight generation from occurring. The third theme present placed importance on the 'documentation and knowledge management' of BA system enhancements so that these are safeguarded in detail if a staff member departs from the organisation.

Other secondary inhibitors were found, which include the 'growing saturation' of BA vendors and tools available for organisations to select from was present. With organisations having a challenging time selecting technology that is best fit for their use. The second theme present involved the need for a 'collaborative workflow' to be present within the organisation, with it being beneficial for BA departments and teams to involve other parts of the business in their work.

Overall the research has highlighted the need for further examination of *BA operations* within organisations, particularly around efficient and effective use of BA resources and measuring value derived from BA use. As business analytics is scalable within organisations, this will prove to be a pivotal challenge to ensure that resource waste is not occurring.

5.6 Organisational Factors

Organisational factors encompasses organisations size, scope and absorptive capacity as well as strategic factors to assist with the successful adoption and use of BA. Corroborations for this value driver include the need for 'strong executive sponsorship' behind BA use within the organisation. This executive commitment and championship towards BA within the organisation should be strongly considered before undertaking such initiatives, as pointed out by the literature (Božič & Dimovski, 2019; Grover et al., 2018; Kiron & Shockley, 2011; LaValle et al., 2011; Ramakrishnan et al., 2012; Ramamurthy et al., 2008; Seddon et al., 2017; Sharma et al., 2007; Tamm et al., 2013; Vidgen et al., 2017; Wang et al., 2019; Wixom et al., 2013). Grover et al. (2018, p. 419) states that "Successful initiatives are usually championed through an integrative BDA strategy and strong leadership". In addition to this literature and participants noted the need for an analytic and 'evidence-based' making culture within the organisation (Buldoo, 2018; Chen et al., 2012; Duan et al., 2018; Grytz & Krohn-Grimberghe, 2018; Holsapple et al., 2014; Kapoor & Kabra, 2014; Krishnamoorthi & Mathew, 2015; Lamba & Dubey, 2015; LaValle et al., 2011; Stevens, 2017; Vidgen et al., 2017). Lamba and Dubey (2015, p. 1) referenced a survey conducted by MIT Centre for Digital Business and McKinsey's business technology office reveals that data-driven organizations are 5% more productive and 6% more profitable than their competitors.

Notably, continued investment in *BA operations* and assets was also a corroboration that appeared (Côrte-Real, Ruivo, Oliveira, et al., 2019; Corte Real et al., 2014; Cosic et al., 2012; Davern & Kauffman, 2000; Kiron & Shockley, 2011; Seddon et al., 2017; Tamm et al., 2013; Wang et al., 2019; Wang & Byrd, 2017; Wang et al., 2015; Wixom et al., 2013; Ylijoki & Porras, 2018; Yoo & Roh, 2018). With Tamm et al. (2013, p. 7) noting that "A key point here is that a significant investment in BI-platform infrastructure, data extraction, and data quality is needed to enable such routine BA use to be easy and secure for end-users."

A theoretical gap existed around the need to align *BA capability* with the strategy and direction of the business was uncovered (Akter et al., 2016; Côrte-Real, Ruivo, & Oliveira, 2019; Côrte-Real, Ruivo, Oliveira, et al., 2019; Cosic et al., 2012; Grover et al., 2018; Moreno et al., 2019) with (Cosic et al., 2012, p. 5) defining this as "The alignment of an organisation's BA initiatives with its business strategy". In summary of this (Lamba & Dubey) point out that "In most of the organization the important decisions are relying on highest paid person's opinion instead of on data Lamba and Dubey (2015, p. 978).

In addition, a practice gap which did not occur in theory surrounded the need for the organisation to be risk-taking in its use of BA. Participant in the study placed importance on being risk-taking with the use of BA projects, as this can ultimately lead to substantial value gains within the organisation.

Some additional challenges and were also identified from the interviews; value inhibitors for organisation factors include the 'importance for a company to place and build up trust in its data'. Respondents noted that this could take up a long time to build up within the organisation; however, this can be quickly lost if integrity is compromised. Also, a theme which supported an organisation with a culture supporting 'data-driven decisions' was also present; otherwise BA insights risk not being acted upon.

To synthesise, our research points towards a strong need for continued top-level support from an executive-level sponsor within an organisation for continued success and value delivery from a business analytic operation. Research into inhibitors for this value driver interestingly uncovered the importance of an organisations trust in data, as well as the need for a supportive organisational culture, surrounding data-driven decision making.

Table 14: Highlights of the research findings

Value Driver	Value Drivers	Value Inhibitors
Definition	People as essential enablers of BA	Culture of Distrust
Data Assets	**Corroborations:** Well Governed Data, Data Integrity, Cloud-Based – Scalable services, Continuous Hardware Improvement **Theoretical Gaps:** High-quality BA/I Technology to fit organisations task and data strategy **Practice Gaps:** Raw Granular Data, Well Documented	**Primary:** Siloed Systems, Legacy Systems, Data Quality **Secondary:** Tech Debt, Fracturing of Technology
Human Capabilities	**Corroborations:** Deep Domain Knowledge **Theoretical Gaps:** Analytical Training **Practice Gaps:** Influential People and Negation Skills, Experimental Nature, Critical Thinking, Strong Data Story	**Primary:** Skilled Analytical Staff to fit industries needs **Secondary:** Staff Retention and Remuneration
BA Impacts	**Corroborations:** Timely Decisions and actions **Theoretical Gaps:** Competitive Position **Practice Gaps:** Business Agility, Defining the Scope of Solution	**Primary:** Accurate, not distorted Presentation, Measuring Value **Secondary:** Meaningful Reporting
BA Operations	**Corroborations:** Data-Driven Organisation, Multidisciplinary Teams, Agile Workflow **Theoretical Gaps:** Innovative workflow **Practice Gaps:** Self-service analytics and reports / Personalisation	**Primary:** Focus on Value Delivery, Budget and Investment in BA, Well Documented system enhancements **Secondary:** Vendor Saturation and Tool selection, Non-Collaborative Workflow
Organisational Factors	**Corroborations:** Executive Sponsorship, Continued Investment in BA within the Organisation **Theoretical Gaps:** Alignment of BA capability with business strategy **Practice Gaps:** Risk-Taking	**Primary:** Company trust in Data **Secondary:** Culture surrounding data-driven decisions

Chapter Six:

Conclusions

This study aimed to understand how value was being derived in organisations and determine key factors that influence this. A review was conducted utilising a framework developed Templier and Paré (2015) to analyse recent scholarly literature relating to the body of knowledge surrounding the topic. From this, five factors were found to impact and influence value generation, Data Assets, Human Capabilities, BA Impacts, BA Operations and Organisational Factors. By collecting qualitative data from business analytic professionals, these factors were subsequently assessed analysed from corroborations and gaps in order to answer the following research question:

"How does Business Analytics contribute to business value in organisations?"

This study gained insight into what ways business analytics can create value and developed an understanding as to what factors influence this. Based on analysing scholarly literature and real-life in-depth interviews, we can conclude that value contribution from a business analytic is highly influenced by all factors uncovered in our study. All of the studied factors were found to have both driving and inhibiting aspects which influence the value generation from business analytics. When examining the evidence, we deem that all of these factors necessary in some extent within organisations in order for value generation to be achieved.

Synthesising our research, we can conclude that the following factors are drivers of value…

Table 15: Synopsis of Business Analytic Value Drivers

Data Assets	Well Governed Data Data Integrity Cloud-Based – Scalable services Continuous Hardware Improvement High-quality BA/I Technology to fit organisations task and data strategy Raw Granular Data Well Documented
Human Capabilities	Deep Domain Knowledge Analytical Training Influential People and Negation Skills Experimental Nature Critical Thinking, Strong Data Story
BA Impacts	Timely Decisions and actions Competitive Position Business Agility Defining the Scope of Solution

BA Operations	Data-Driven Organisation Multidisciplinary Teams Agile Workflow Innovative workflow Self-service analytics and reports / Personalisation
Organisational Factors	Executive Sponsorship Continued Investment in BA within the Organisation Alignment of BA capability with business strategy Risk-Taking

Synthesising our research, we can conclude that the following factors are inhibitors of value…

Table 16: Synopsis of Business Analytic Value Inhibitors

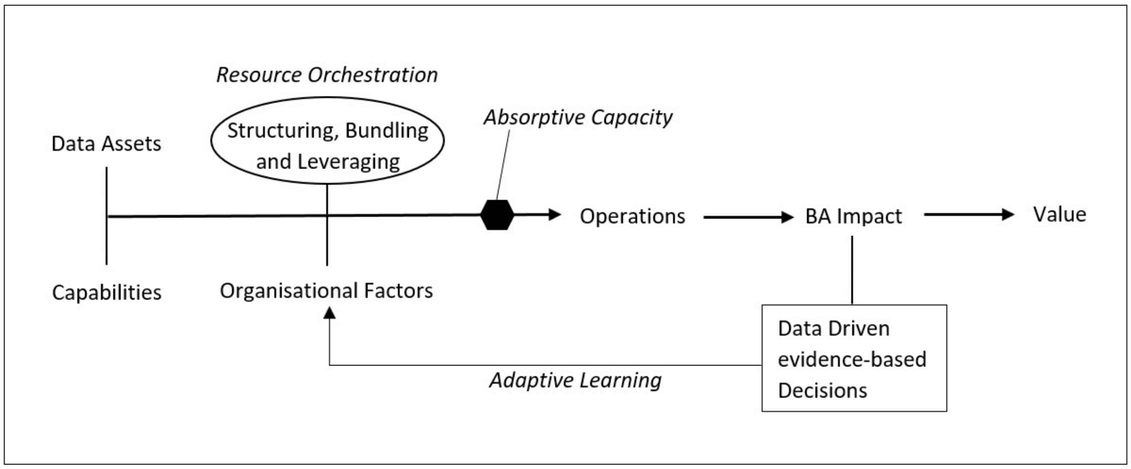
Data Assets	Siloed Systems Legacy Systems Data Quality Tech Debt Fracturing of Technology
Human Capabilities	Skilled Analytical Staff to fit industry needs Staff Retention Remuneration
BA Impacts	Accurate, not distorted presentation Measuring Value Meaningful Reporting
BA Operations	Focus on Value Delivery Budget and Investment in BA Well Documented System Enhancements Vendor Saturation and Tool Selection Non-Collaborative Workflow
Organisational Factors	Company Trust in Data Culture Surrounding data-driven decisions

6.1 Theoretical Contributions:

Emerging from this study, it is evident that there is a gap between the academic and professional stream of knowledge and the factors supporting value generation. We believe that positive results could be achieved by bridging them together to a greater extent. By conducting research with a greater socio-technical approach, more applicable and transferable findings could potentially occur. Hence, this thesis provides the first step in the aim of bridging these literature streams and an initial attempt in addressing the encountered gap. As previous theory is lacking a more comprehensive view on the factors that influence value generation from business analytics within organisations, due to prior studies primary focusing on one or two aspects of, this study by testing and validating prior studies in this domain and by providing a holistic view. Thus, this study contributes to the existing literature on Business Analytics use.

Drawing from our conclusions, we theorised the below model, synthesising the steps in which business analytics generates value in organisations. In order to explain our model further, we use the resource orchestration framework as a mediating factor and lens to explain business analytic value generation and orchestrate analytic assets and factors.

Figure 11: Business Analytics Value Generation Model



6.2 Implications for Practice:

This study gives managerial implications for utilising or adopting business analytics within their organisation. It can be used by managers and executives for making implementation strategies and analysing the impact of each factor and relating drivers. The role of absorptive capacity within an organisation is key in order for organisations to constructively build decision making processes to drive strategy, with adaptive learning being a cornerstone in this cycle. Though this research 'People' have been highlighted as a critical success factor, with people classed as drivers of assets as well as capabilities within the organisation. 'People' become the sources of Data, Information, Knowledge and Wisdom (DIRW Pyramid) within organisations as these are the people who interpret the data, using their absorptive and transformative abilities.

> *"it is people who look at the data, assign meaning to it, search for patterns, sense opportunities and so on. Further, it is people – with all their different knowledge and cognitive capabilities and limitations – who derive insights" (Seddon et al., 2017, p. 248)*

Resource orchestration theory gives a good holistic view of the environment and factors through the structuring, bundling and leveraging divisions. However, one should be aware that the framework itself is rather broad and mainly ignores the technical factors. This study can further be used by other players in the ecosystem, such as the data professionals or organisations looking to adopt the technology, as the results touch upon potential value drivers or inhibitors coming from the collaboration with them. This could help the ecosystem to think how to ease the processes of implementing a successful and sustained business analytics program without the high degree of failures within organisations currently present. The resource orchestration framework as a managerial tool provides a good sense for creating implementation strategies and reviewing the contexts.

6.3 Limitations:

This research has some limitations that need consideration. Firstly, the participants interviewed with our study were based within New Zealand. Although this was not seen as a large issue as participants included within the study brought experience from working in other countries, this aspect could have been potentially studied further, as some themes in factors may have been affected by this. Secondly, the framework used for this study is rather broad in nature, as a great wealth of information is contained in each of the five factors which were studied. As an alternative, we could have focused solely on one or two factors. However, as the previous research is lacking a holistic view of channels for value generation and the pitfalls towards reaching this, thus we wanted to address this gap by exploring the influence of all five factors. Lastly, while some quality assurance has been undertaken within the study, there are some limitations. Something that could also be reflected upon is the nature of qualitative studies and how the findings are based on the researchers own interpretations. Hence, future research is encouraged to validate the findings further.

6.4 Future Research:

This study contributes to the existing body of literature within Business Analytics, Value generation and inhibitors. Other researchers interested in the topic can use it for their own field studies by building upon this research. Future studies could investigate this topic by taking the perspective of other organisations in differing ecosystems and countries, or by including more entities in the study. Especially contrasting our findings against similar studies from other academic's perspectives would presumably provide valuable insights. Although this study touched upon the domains of implementation and setting, the main focus of this study was on the role of the factors and subsequent value generation. Hence this leaves room for further research gaining a more in-depth understanding of these aspects.

6.5 Concluding Remarks:

Overall this study has contributed to research through an examination of current literature on the topic as well as a detailed gap analysis between research and practice through semi structured interviews and subsequent thematic analysis. The incorporation of IS factors can help managers and executives making implementation strategies and analysing the impact of each factor and relating drivers. From this study, several theoretical and practical contributions are made in the field of business analytics and value creation. This research also had limitations and was not all-encompassing; therefore, there is room for improvement and for future research to build upon the findings of this study. Practice and research both make substantial contributions towards the development of the field, thus further research should be conducted on this topic. To conclude a notable quote from both research and practice is presented below…

“it is important to point out that insights occur in people’s heads, not in computers”
(Seddon et al., 2017, p. 249)

“Let's use business analytics, and let's make a decision. Then you look back at the decision and go, well, did that help us remove cost? Did it help us improve service or efficiency? Did we do it for less? Did we do it better, quicker, faster? Or with a better outcome for customers? Or has that enabled us to make a better decision? That’s how I would define success.” (Research Participant)

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Annex A: Research Invitation and Interview Template

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Telephone: +64 226419388

Email: fraser.beckwith@pg.canterbury.ac.nz

Date: 27/08/19
HEC Ref: HEC 2019/34/LR

UNIVERSITY OF CANTERBURY
Te Whare Wānanga o Waitaha
CHRISTCHURCH NEW ZEALAND

How Business Analytics contributes to value in Organisations? Research Information Sheet

To whom it may concern, I'm Fraser Beckwith a current master's student at the University of Canterbury. As part of my master's studies, I'm writing a thesis, completing research on "How Business Analytics contributes to business value in Organisations?". From this I will be looking at developing a narrative on good practices and lessons learned from Business Analytics and develop at framework of analytics "value drivers". With the goal of helping Senior executives and managers gain a clearer understanding of how organisation can realise business value from BA, and how to realise greater value in the future. You have been approached to take part in this study because your knowledge surrounding business analytics.

If you choose to take part in this study, your involvement in this project will be to take part in a 1-hour interview where you will be asked a number of questions about business analytics and its use. The interview will be audio recorded for transcribing and analysis with your permission, and interviews will be transcribed verbatim.

Participation is voluntary and you have the right to withdraw at any stage without penalty. You may ask for your raw data to be returned to you or destroyed at any point. If you withdraw, I will remove information relating to you. However, once analysis of raw data starts on 20th of September it will become increasingly difficult to remove the influence of your data on the results.

The results of the project may be published, but you may be assured of the complete confidentiality of data gathered in this investigation. To ensure confidentiality, only myself and my two thesis supervisors will have access to the data. While undertaking this research, the data obtained will be securely stored and kept confidential, with this data being retained in accordance to the University of Canterbury's guidelines. All storage facilities including electronic equipment will be in rooms that can be locked. All data will be stored in password-protected files and, where on computers, the computers should be password protected. Data pertaining to the research will be backed up or stored on the University servers for five years before deletion. The final thesis is a public document and will be available through the UC Library.

Please indicate to the researcher on the consent form if you would like to receive a copy of the summary of results of the project.

The project is being carried out as a requirement of a Master of Commerce degree at the Univertsity of Canterbury by Fraser Beckwith under the supervision of Ravi Sharma and Stephen Wingreen, who can be contacted at ravishankar.sharma@canterbury.ac.nz or stephen.wingreen@canterbury.ac.nz . Both will be pleased to discuss any concerns you may have about participation in the project.

This project has been reviewed and approved by the University of Canterbury Human Ethics Committee, and participants should address any complaints to The Chair, Human Ethics Committee, University of Canterbury, Private Bag 4800, Christchurch (human-ethics@canterbury.ac.nz).

If you agree to participate in the study, you are asked to complete the consent form and return to

fraser.beckwith@pg.canterbury.ac.nz via email

How Business Analytics contributes to value in Organisations?

Consent Form for interview participants

- ☐ I have been given a full explanation of this project and have had the opportunity to ask questions.
- ☐ I understand what is required of me if I agree to take part in the research.
- ☐ I consent to audio recording of this interview for transcribing purposes
- ☐ I understand that participation is voluntary and I may withdraw at any time without penalty. Withdrawal of participation will also include the withdrawal of any information I have provided should this remain practically achievable.
- ☐ I understand that any information or opinions I provide will be kept confidential to the researcher and thesis supervisors, and that any published or reported results will not identify the participants or organisation. I understand that a thesis is a public document and will be available through the UC Library.
- ☐ I understand that all data collected for the study will be kept in locked and secure facilities and/or in password protected electronic form and will be destroyed after five years.
- ☐ I understand the risks associated with taking part and how they will be managed.
- ☐ I understand that I can contact the researcher (Fraser Beckwith at fraser.beckwith@pg.canterbury.ac.nz) or supervisor (Ravishankar Sharma at ravishankar.sharma@canterbury.ac.nz . He will be pleased to discuss any concerns you may have about) for further information. If I have any complaints, I can contact the Chair of the University of Canterbury Human Ethics Committee, Private Bag 4800, Christchurch (human-ethics@canterbury.ac.nz)
- ☐ I would like a summary of the results of the project, via a link to the UC library thesis once available.
- ☐ By signing below, I agree to participate in this research project.

Name:_____________________________Signed:___________________________Date: ___________________________________

Email address *(for report of findings, if applicable)*:
____

If you agree to participate in the study, you are asked to complete the consent form and return to fraser.beckwith@pg.canterbury.ac.nz via email

Department of Accounting and Information Systems
Telephone: +64 226419388

Email: fraser.beckwith@pg.canterbury.ac.nz

UNIVERSITY OF CANTERBURY
Te Whare Wānanga o Waitaha
CHRISTCHURCH NEW ZEALAND

How does Business Analytics contribute to value in Organisations?

Interview Template:

- ☐ What is your understanding of business intelligence and analytics? How does BI&A add value to your organisation?
- ☐ To ensure a common understanding of the term, we suggest the following theory-based definition: "Business intelligence and analytics (BI&A) refer to the techniques, technologies, systems, practices, methodologies, and applications that analyse critical business data to help an enterprise better understand its business and market and make timely business decisions" (Chen et al., 2012, p. 1166).
- ☐ How would you define success of a BI&A implementation?
- ☐ Which BI&A techniques you do widely use in your organisation?
- ☐ How does BI&A use result in insight generation in your organisation?
- ☐ How do you use BI&A generated insights?
- ☐ What are some key requirements to gather and process data into valuable knowledge?
- ☐ What skills requirements need to be met for BI&A facilitated decisions?
- ☐ What organisational factors influence the value creation process?
- ☐ What are the main problems that you have encountered?
- ☐ Are there any other inhibitors to the value of BI&A?
- ☐ Are there any other comments that you would like to add relating to the value of BI&A?

Annex B: HEC Approval

UNIVERSITY OF CANTERBURY
Te Whare Wānanga o Waitaha
CHRISTCHURCH NEW ZEALAND

HUMAN ETHICS COMMITTEE

Secretary, Rebecca Robinson
Telephone: +64 03 369 4588, Extn 94588
Email: human-ethics@canterbury.ac.nz

Ref: HEC 2019/34/LR

15 July 2019

Fraser Beckwith
Accounting and Information Systems
UNIVERSITY OF CANTERBURY

Dear Fraser

Thank you for submitting your low risk application to the Human Ethics Committee for the research proposal titled "How does Business Analytics contribute to value in organisations?".

I am pleased to advise that this application has been reviewed and approved.

Please note that this approval is subject to the incorporation of the amendments you have provided in your email of 10th July 2019.

With best wishes for your project.

Yours sincerely

Dr Dean Sutherland
Chair, Human Ethics Committee

University of Canterbury Private Bag 4800, Christchurch 8140, New Zealand. www.canterbury.ac.nz

Annex C: Thematic Word Cloud’s

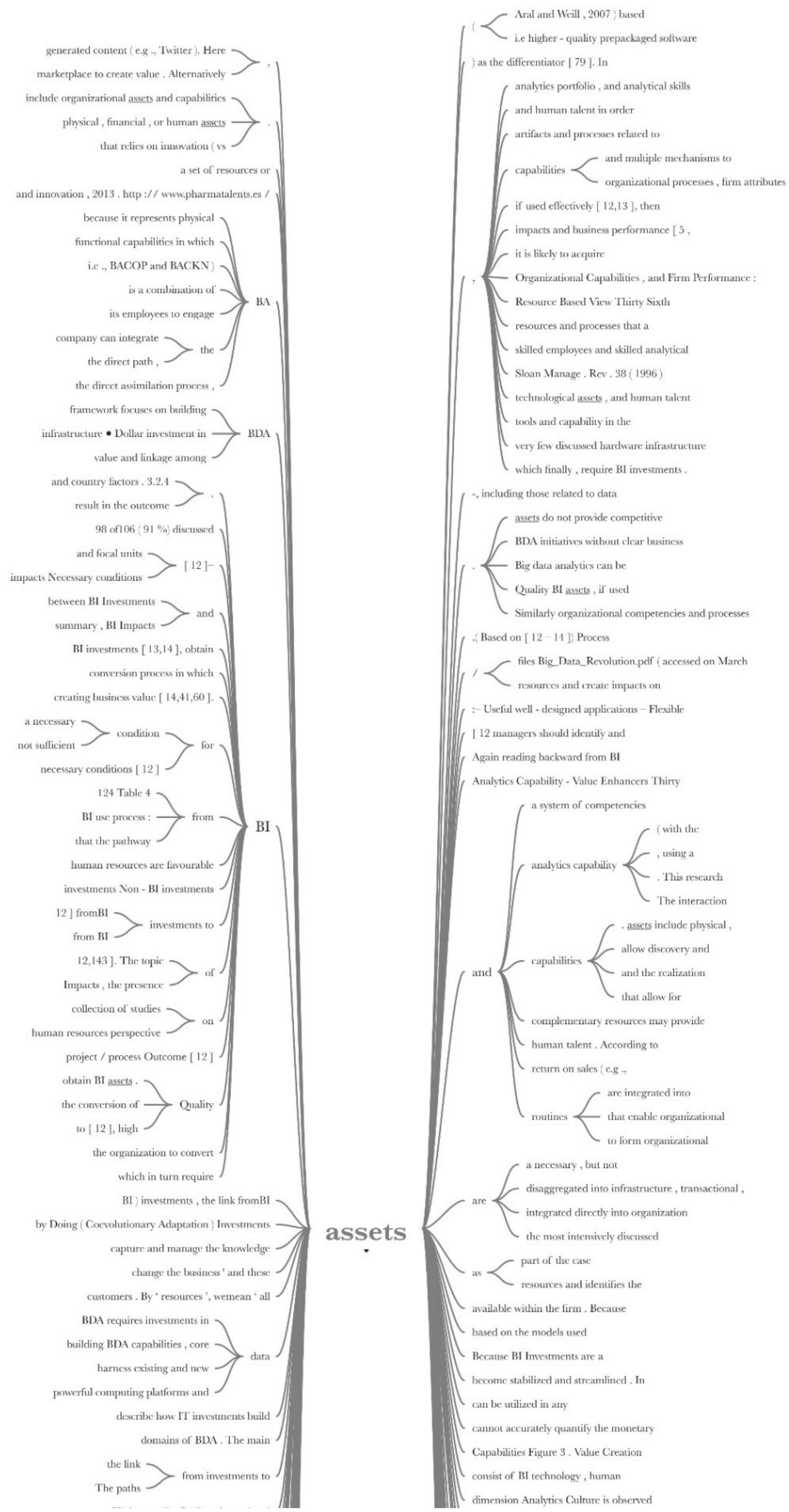
Word Cloud: Literature

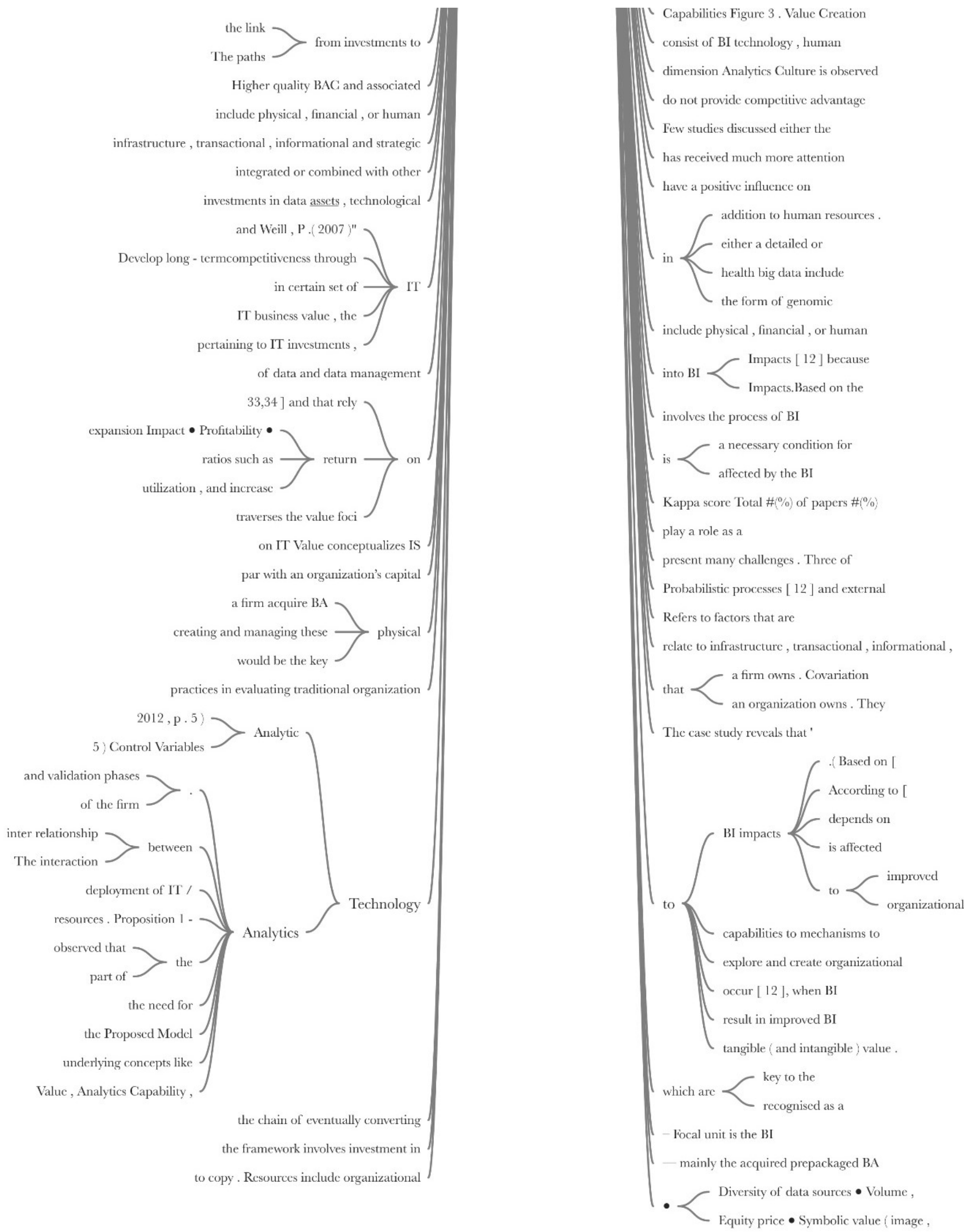
Word Cloud: Participant Interviews

Annex D: Literature NVivo Analysis

Note due to HEC guidelines only a selection of our NVivo analysis is suitable for inclusion in the study.

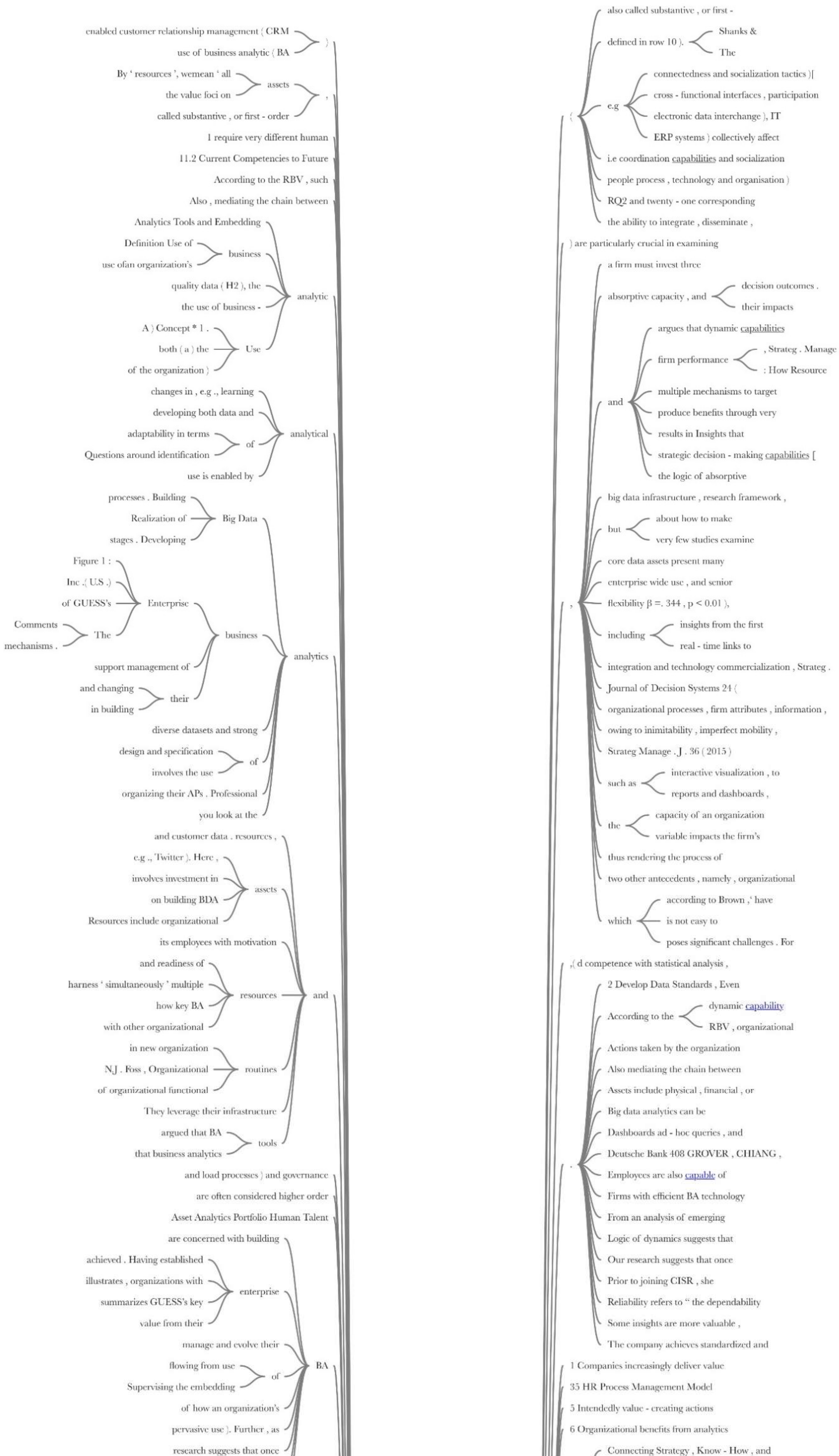
Semantic Network Diagram for label = Assets

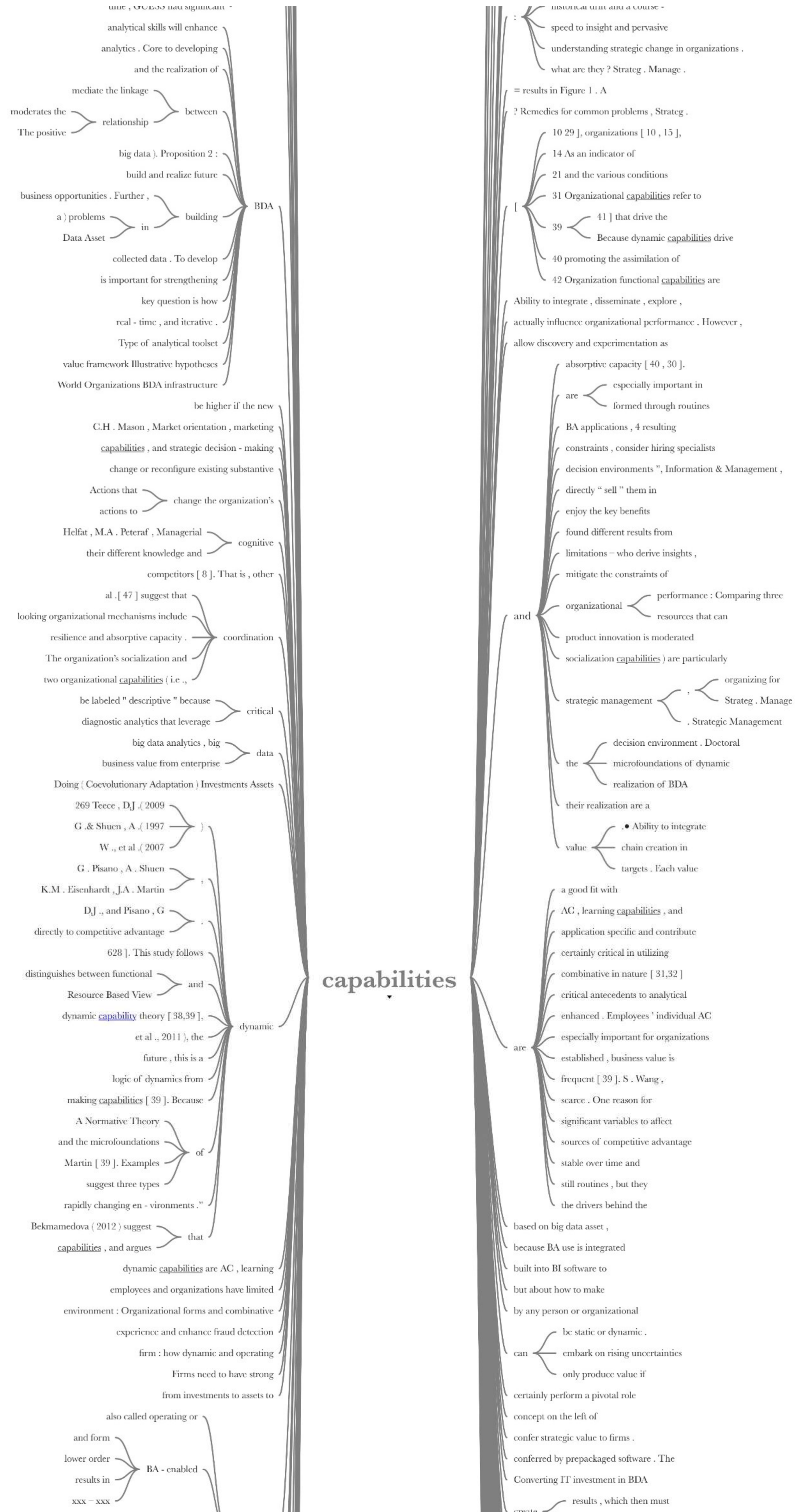


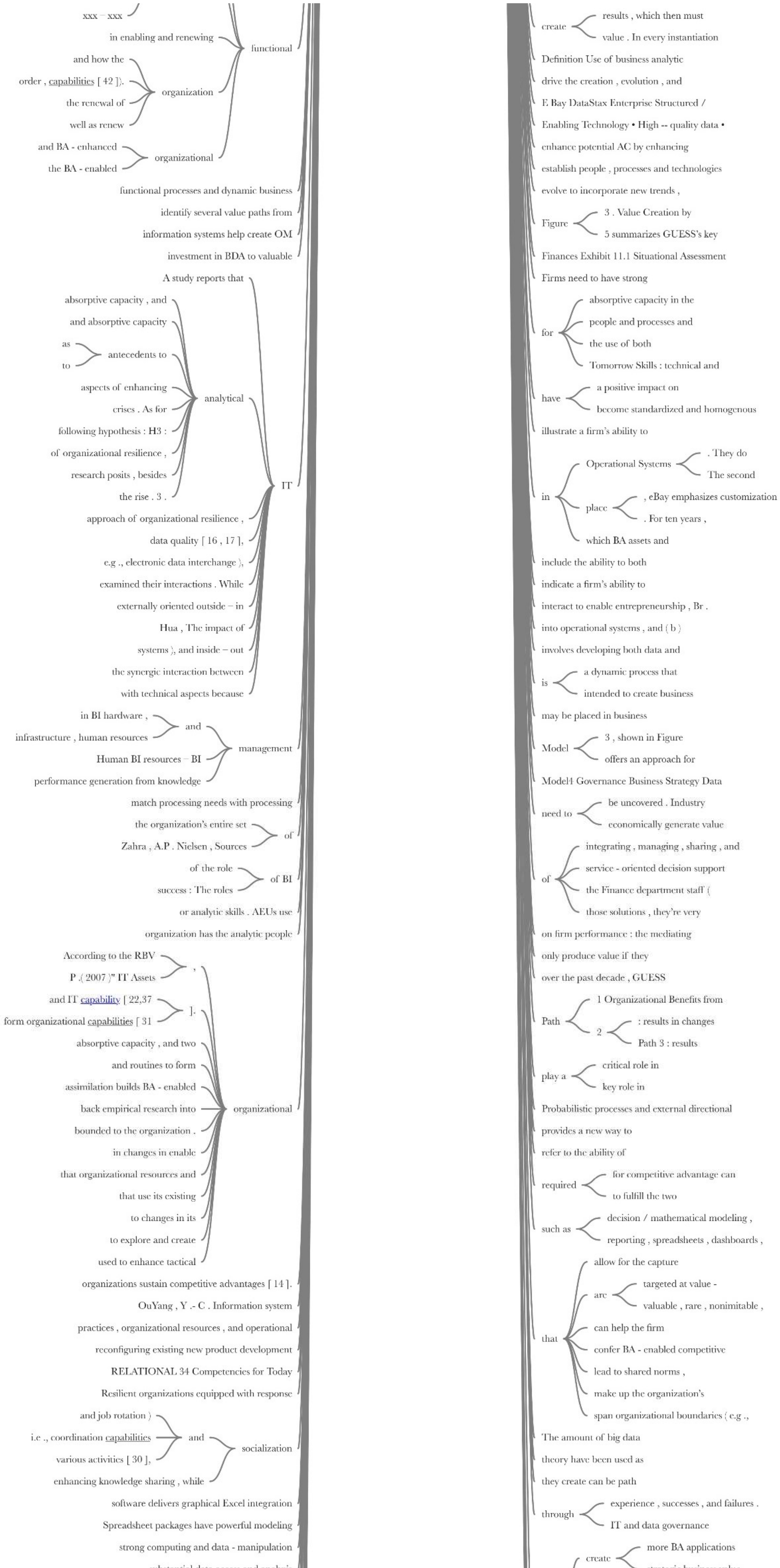


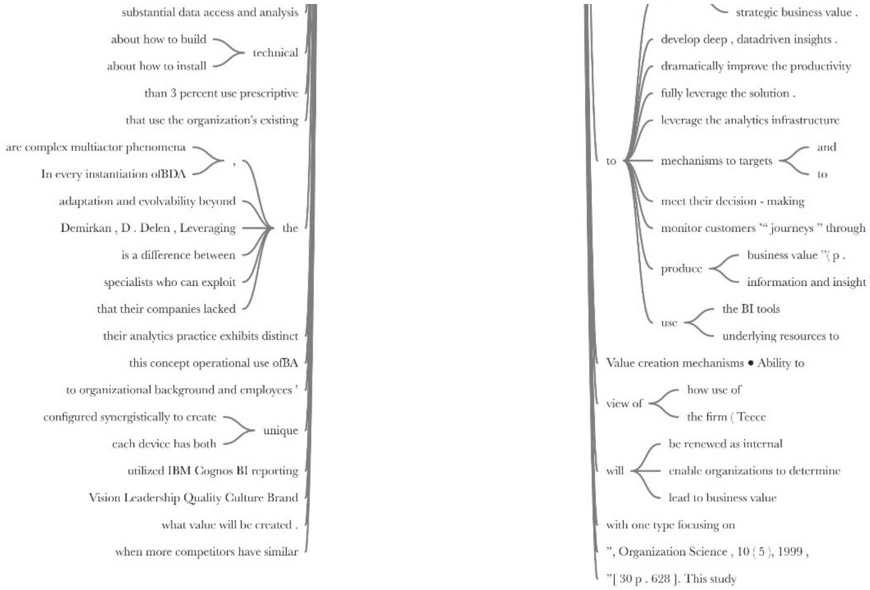
the link
The paths
from investments to
Higher quality BAC and associated
include physical , financial , or human
infrastructure , transactional , informational and strategic
integrated or combined with other
investments in data assets , technological
and Weill , P .(2007)"
Develop long - termcompetitiveness through
in certain set of
IT
IT business value , the
pertaining to IT investments ,
of data and data management
33,34] and that rely
expansion Impact • Profitability •
ratios such as
return
on
utilization , and increase
traverses the value foci
on IT Value conceptualizes IS
par with an organization's capital
a firm acquire BA
creating and managing these
physical
would be the key
practices in evaluating traditional organization
2012 , p . 5)
Analytic
5) Control Variables
and validation phases
.
of the firm
inter relationship
between
The interaction
deployment of IT /
Technology
resources . Proposition 1 -
Analytics
observed that
the
part of
the need for
the Proposed Model
underlying concepts like
Value , Analytics Capability ,
the chain of eventually converting
the framework involves investment in
to copy . Resources include organizational
Capabilities Figure 3 . Value Creation
consist of BI technology , human
dimension Analytics Culture is observed
do not provide competitive advantage
Few studies discussed either the
has received much more attention
have a positive influence on
in
addition to human resources .
either a detailed or
health big data include
the form of genomic
include physical , financial , or human
into BI
Impacts [12] because
Impacts.Based on the
involves the process of BI
is
a necessary condition for
affected by the BI
Kappa score Total #(%) of papers #(%)
play a role as a
present many challenges . Three of
Probabilistic processes [12] and external
Refers to factors that are
relate to infrastructure , transactional , informational ,
that
a firm owns . Covariation
an organization owns . They
The case study reveals that '
to
BI impacts
.(Based on [
According to [
depends on
is affected
to
improved
organizational
capabilities to mechanisms to
explore and create organizational
occur [12], when BI
result in improved BI
tangible (and intangible) value .
which are
key to the
recognised as a
– Focal unit is the BI
— mainly the acquired prepackaged BA
•
Diversity of data sources • Volume ,
Equity price • Symbolic value (image ,

Semantic Network Diagram for label = Capabilities

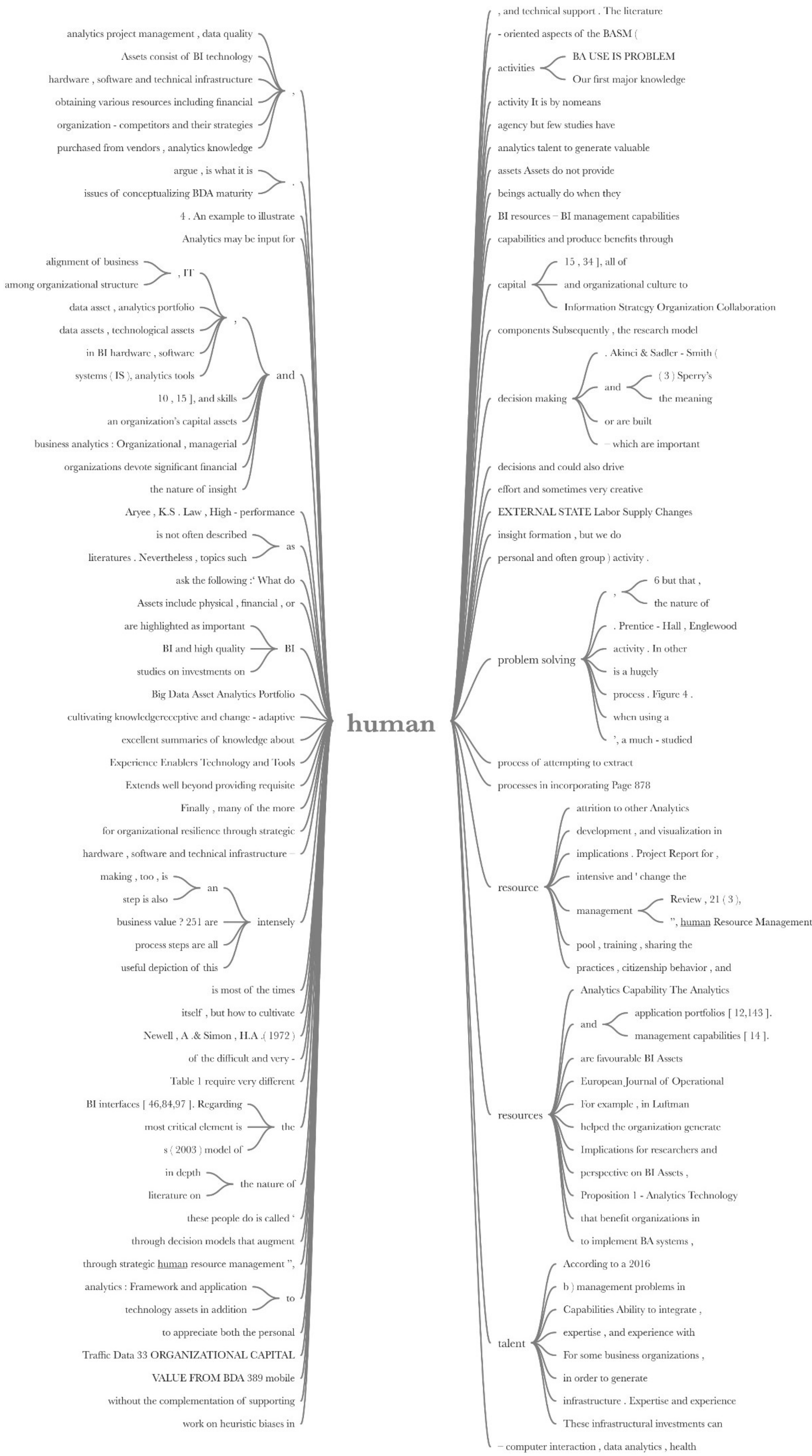



analytical skills will enhance
analytics . Core to developing
and the realization of
mediate the linkage
moderates the
The positive
relationship
between
big data). Proposition 2 :
build and realize future
business opportunities . Further ,
a) problems
Data Asset
in
building
BDA
collected data . To develop
is important for strengthening
key question is how
real - time , and iterative .
Type of analytical toolset
value framework Illustrative hypotheses
World Organizations BDA infrastructure
be higher if the new
C.H . Mason , Market orientation , marketing
capabilities , and strategic decision - making
change or reconfigure existing substantive
Actions that
actions to
change the organization's
Helfat , M.A . Peteraf , Managerial
their different knowledge and
cognitive
competitors [8]. That is , other
al .[47] suggest that
looking organizational mechanisms include
resilience and absorptive capacity .
The organization's socialization and
two organizational capabilities (i.e .,
coordination
be labeled " descriptive " because
diagnostic analytics that leverage
critical
big data analytics , big
business value from enterprise
data
Doing (Coevolutionary Adaptation) Investments Assets
269 Teece , D.J .(2009
G .& Shuen , A .(1997
W ., et al .(2007
)
G . Pisano , A . Shuen
K.M . Eisenhardt , J.A . Martin
,
D.J ., and Pisano , G
directly to competitive advantage
.
628]. This study follows
distinguishes between functional
Resource Based View
and
dynamic capability theory [38,39],
et al ., 2011), the
future , this is a
logic of dynamics from
making capabilities [39]. Because
dynamic
A Normative Theory
and the microfoundations
Martin [39]. Examples
suggest three types
of
rapidly changing en - vironments ."
Bekmamedova (2012) suggest
capabilities , and argues
that
dynamic capabilities are AC , learning
employees and organizations have limited
environment : Organizational forms and combinative
experience and enhance fraud detection
firm : how dynamic and operating
Firms need to have strong
from investments to assets to
also called operating or
and form
lower order
results in
xxx – xxx
BA - enabled
capabilities
historical drift and a course -
speed to insight and pervasive
understanding strategic change in organizations .
what are they ? Strateg . Manage .
:
= results in Figure 1 . A
? Remedies for common problems , Strateg .
10 29], organizations [10 , 15],
14 As an indicator of
21 and the various conditions
31 Organizational capabilities refer to
41] that drive the
Because dynamic capabilities drive
39
40 promoting the assimilation of
42 Organization functional capabilities are
[
Ability to integrate , disseminate , explore ,
actually influence organizational performance . However ,
allow discovery and experimentation as
absorptive capacity [40 , 30].
especially important in
formed through routines
are
BA applications , 4 resulting
constraints , consider hiring specialists
decision environments ", Information & Management ,
directly " sell " them in
enjoy the key benefits
found different results from
limitations – who derive insights ,
mitigate the constraints of
performance : Comparing three
resources that can
organizational
product innovation is moderated
socialization capabilities) are particularly
organizing for
Strateg . Manage .
,
. Strategic Management
strategic management
decision environment . Doctoral
microfoundations of dynamic
realization of BDA
the
their realization are a
.• Ability to integrate
chain creation in
targets . Each value
value
and
a good fit with
AC , learning capabilities , and
application specific and contribute
certainly critical in utilizing
combinative in nature [31,32]
critical antecedents to analytical
enhanced . Employees ' individual AC
especially important for organizations
established , business value is
frequent [39]. S . Wang ,
scarce . One reason for
significant variables to affect
sources of competitive advantage
stable over time and
still routines , but they
the drivers behind the
are
based on big data asset ,
because BA use is integrated
built into BI software to
but about how to make
by any person or organizational
be static or dynamic .
embark on rising uncertainties
only produce value if
can
certainly perform a pivotal role
concept on the left of
confer strategic value to firms .
conferred by prepackaged software . The
Converting IT investment in BDA
results , which then must
create

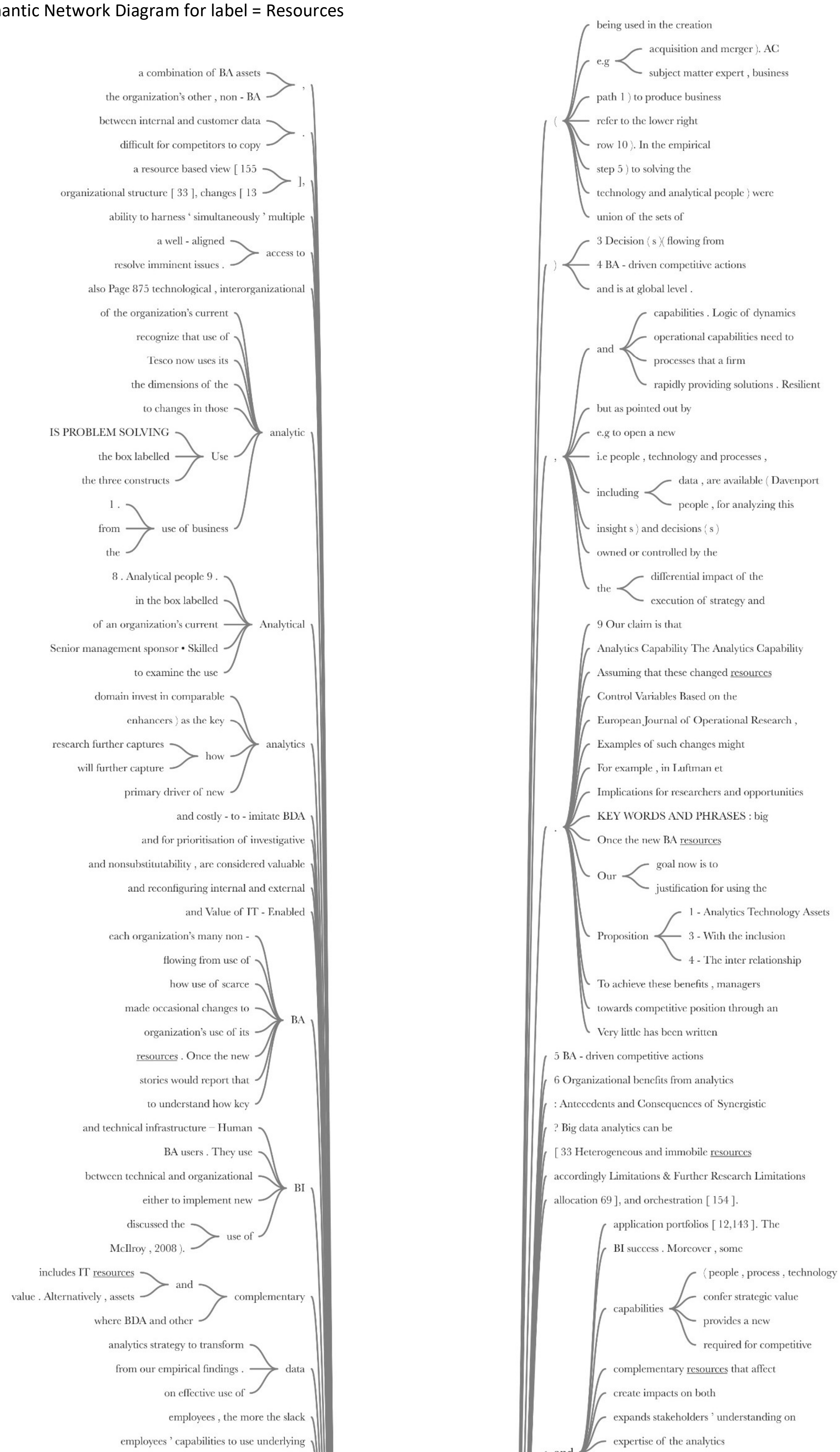

xxx – xxx
in enabling and renewing
functional
and how the
order , capabilities [42]).
organization
the renewal of
well as renew
and BA - enhanced
organizational
the BA - enabled
functional processes and dynamic business
identify several value paths from
information systems help create OM
investment in BDA to valuable
A study reports that
absorptive capacity , and
and absorptive capacity
as
antecedents to
to
aspects of enhancing
analytical
crises . As for
following hypothesis : H3 :
of organizational resilience ,
research posits , besides
the rise . 3 .
IT
approach of organizational resilience ,
data quality [16 , 17],
e.g ., electronic data interchange),
examined their interactions . While
externally oriented outside – in
Hua , The impact of
systems), and inside – out
the synergic interaction between
with technical aspects because
in BI hardware ,
and
infrastructure , human resources
management
Human BI resources – BI
performance generation from knowledge
match processing needs with processing
the organization's entire set
of
Zahra , A.P . Nielsen , Sources
of the role
of BI
success : The roles
or analytic skills . AEUs use
organization has the analytic people
According to the RBV
,
P .(2007)" IT Assets
and IT capability [22,37
].
form organizational capabilities [31
absorptive capacity , and two
and routines to form
assimilation builds BA - enabled
back empirical research into
organizational
bounded to the organization .
in changes in enable
that organizational resources and
that use its existing
to changes in its
to explore and create
used to enhance tactical
organizations sustain competitive advantages [14].
OuYang , Y .- C . Information system
practices , organizational resources , and operational
reconfiguring existing new product development
RELATIONAL 34 Competencies for Today
Resilient organizations equipped with response
and job rotation)
i.e ., coordination capabilities
and
socialization
various activities [30],
enhancing knowledge sharing , while
software delivers graphical Excel integration
Spreadsheet packages have powerful modeling
strong computing and data - manipulation
create
results , which then must
value . In every instantiation
Definition Use of business analytic
drive the creation , evolution , and
E Bay DataStax Enterprise Structured /
Enabling Technology • High -- quality data •
enhance potential AC by enhancing
establish people , processes and technologies
evolve to incorporate new trends ,
Figure
3 . Value Creation by
5 summarizes GUESS's key
Finances Exhibit 11.1 Situational Assessment
Firms need to have strong
for
absorptive capacity in the
people and processes and
the use of both
Tomorrow Skills : technical and
have
a positive impact on
become standardized and homogenous
illustrate a firm's ability to
in
Operational Systems
. They do
The second
place
, eBay emphasizes customization
. For ten years ,
which BA assets and
include the ability to both
indicate a firm's ability to
interact to enable entrepreneurship , Br .
into operational systems , and (b)
involves developing both data and
is
a dynamic process that
intended to create business
may be placed in business
Model
3 , shown in Figure
offers an approach for
Model4 Governance Business Strategy Data
need to
be uncovered . Industry
economically generate value
of
integrating , managing , sharing , and
service - oriented decision support
the Finance department staff (
those solutions , they're very
on firm performance : the mediating
only produce value if they
over the past decade , GUESS
Path
1 Organizational Benefits from
2
: results in changes
Path 3 : results
play a
critical role in
key role in
Probabilistic processes and external directional
provides a new way to
refer to the ability of
required
for competitive advantage can
to fulfill the two
such as
decision / mathematical modeling ,
reporting , spreadsheets , dashboards ,
that
allow for the capture
are
targeted at value -
valuable , rare , nonimitable ,
can help the firm
confer BA - enabled competitive
lead to shared norms ,
make up the organization's
span organizational boundaries (e.g .,
The amount of big data
theory have been used as
they create can be path
through
experience , successes , and failures .
IT and data governance
create
more BA applications


substantial data access and analysis
about how to build
about how to install
technical
than 3 percent use prescriptive
that use the organization's existing
are complex multiactor phenomena
In every instantiation ofBDA
,
adaptation and evolvability beyond
Demirkan , D . Delen , Leveraging
is a difference between
specialists who can exploit
that their companies lacked
the
their analytics practice exhibits distinct
this concept operational use ofBA
to organizational background and employees '
configured synergistically to create
each device has both
unique
utilized IBM Cognos BI reporting
Vision Leadership Quality Culture Brand
what value will be created .
when more competitors have similar
strategic business value .
develop deep , datadriven insights .
dramatically improve the productivity
fully leverage the solution .
leverage the analytics infrastructure
to
mechanisms to targets
and
to
meet their decision - making
monitor customers '" journeys " through
produce
business value "(p .
information and insight ",
use
the BI tools
underlying resources to
Value creation mechanisms • Ability to
view of
how use of
the firm (Teece
will
be renewed as internal
enable organizations to determine
lead to business value
with one type focusing on
", Organization Science , 10 (5), 1999 ,
"[30 p . 628]. This study

Semantic Network Diagram for label = Human



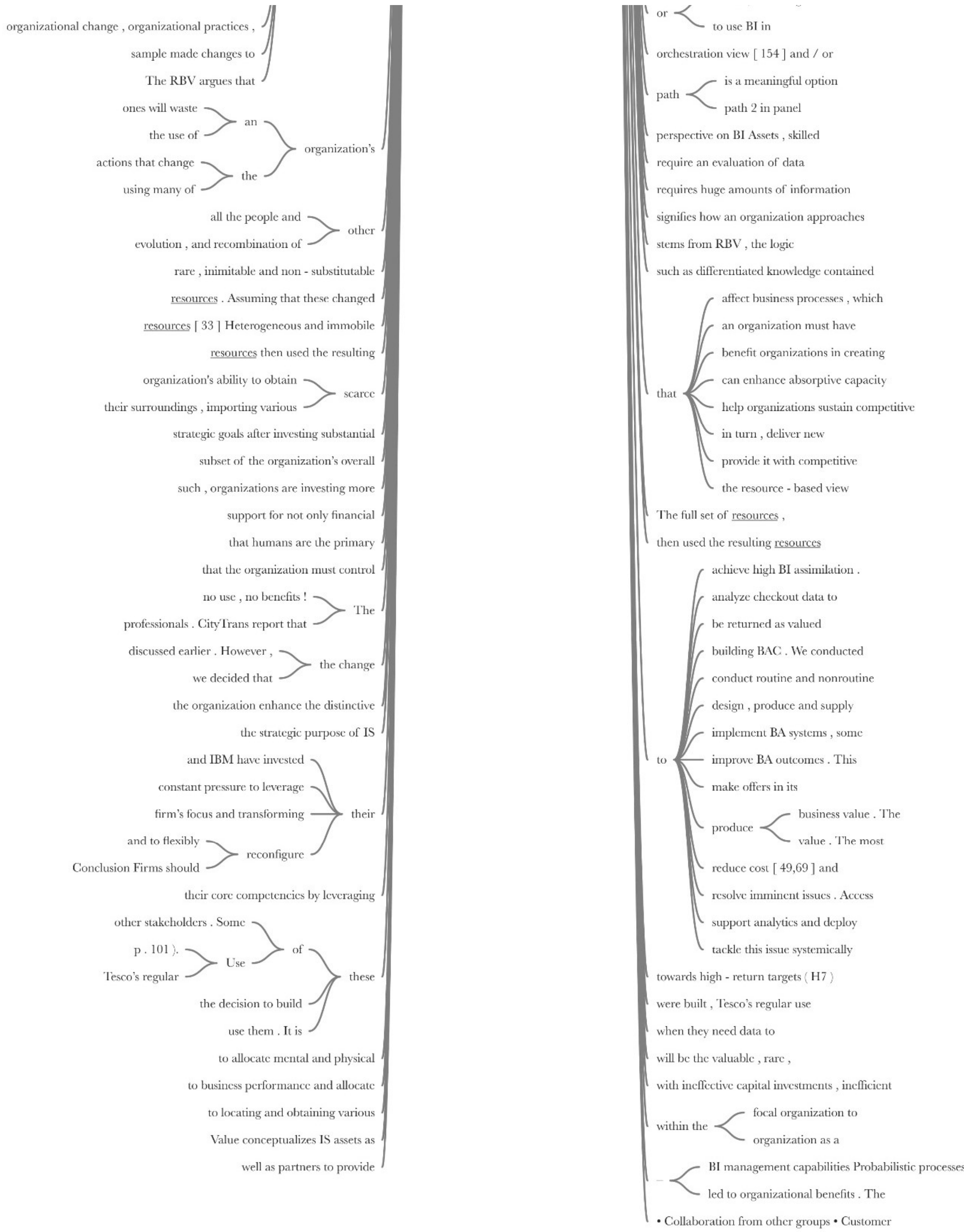
Semantic Network Diagram for label = Resources



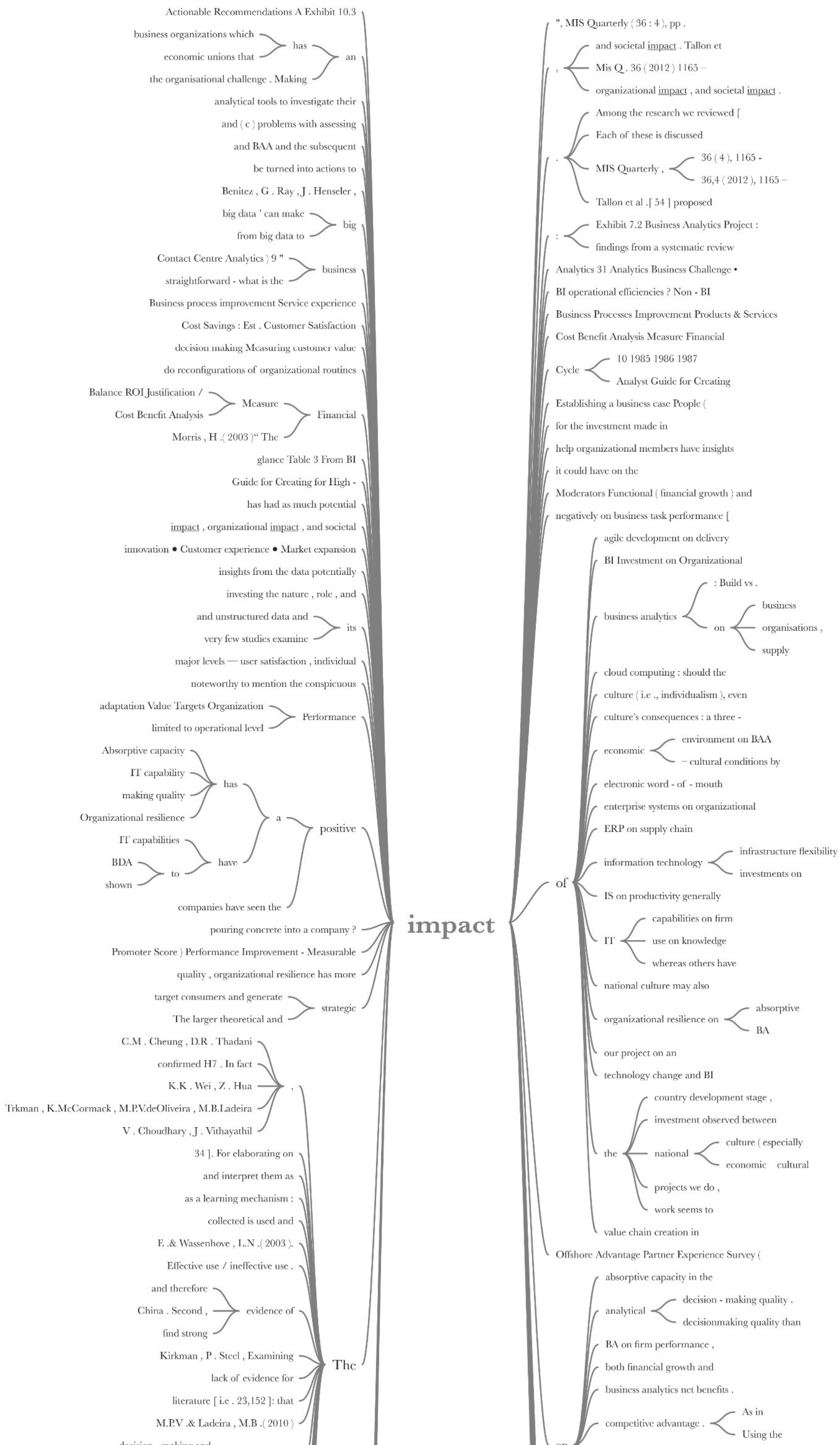
enterprise - wide orientation (H6), direct
2012a , 2012b), many use
Path 1 usage leverages
existing
105 .[30] J . Barney ,
376 . Barney , J.B .(1991)
780 . Barney , J .(1991)"
Firm
focal organization uses its many
form of head count or
have the capability to devote
how IT investments build assets /
consist of BI technology
software and technical infrastructure
,
BI hardware , software
of business , IT
,
devote significant financial
and
and high quality
highlighted as important
on investments on
BI
interfaces [46,84,97]. Regarding the
assets in addition
Framework and application
to
human
immediately assessing problems , effectively organizing
implementation . The embeddedness of BAC
in which information systems (IS)
resource perspective , which includes
study has further conceptualized
IT
and analytical people are
delivery schedule Identify your
key
market opportunities through flexibly combining
more effectively or with fewer
more likely the organization devotes
not committed to provide
potential and whether the
necessary
need to ' strategically align ' all
obtaining and allocating scarce storage
31,32] and the combination
addition , the efficient mobility
in organizations . The logic
leads to the embeddedness
science solutions), co - location
comprised of a
resources The full
that organization's entire
set
the gain and release
the importance and readiness
the reallocation and restructuring
of
of other resources into new
of Value Creation Logics Explanation
or configuration of tangible , intangible
organization . The BASM assumes that
7 and 8)
7 and 8 .
10
of extant IT platforms
.
actions that use existing
creating actions that
competitive actions
driven decision
to
change
et al ., 2004).
external factors , including
complementary
hypotheses BDA capabilities and
in a change
lead to changes
in
it to create new
of BDA with other
organizational

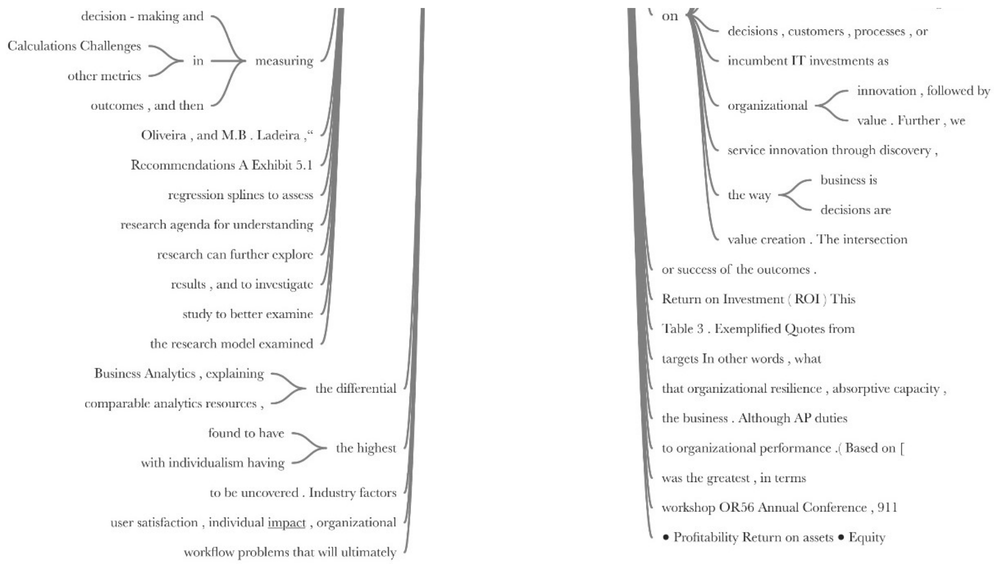
resources

and
identifies the strategic purpose
learning by doing . Consistency
management capabilities [14]. As
organization routines , they are
organizational capabilities that are
productively turn them into
shown how much personal
sustained competitive advantage
", Journal
, J .
. Journal
are
driven by people and
favourable BI Assets which
as a
combination of investment
product , or for
at Tesco was based on
but also Page 875 technological ,
by
any organizational unit to
people in
different parts
many different
their organization's customers , not
can be configured synergistically to
confer strategic value to organizations [
construct at the top left
contribute to business performance by
Decisions flowing from insights flowing
due to a high level
enable the organization to operate
enables the firm to survive
enhances a firm's ability to
flexibly based upon changing market
flowing from use of BA .
for
BAA . 4.2 . Data collection
BI success [35,49,83,96] such
months before changing them
technical improvements . BA use
the
analytics needs . While
firm (Wade and
generate higher value . Relevance to
helped the organization generate more
in
a firm [5]. When
functional activities leads to
order to
achieve supernormal
use them .
the lower left of
include organizational
assets and capabilities .
structure , policies and
including financial , human , and technical
influencing the Business Performance of
into
BA as part of
desired outputs . Figure 4
new
resources and organization
sources of competitive
realization . Vision salience plays
involved in BA usage are
it owns and the more
leads to the embeddedness of
Locate delivery channels & tools Lay
may
provide symbolic value to
sometimes lead directly to
means usage of BI technology
might result in competitive advantage .
needed to work the land
of the firm and its
assets -, including those related


organizational change , organizational practices ,
sample made changes to
The RBV argues that
ones will waste
the use of
an
organization's
actions that change
using many of
the
all the people and
evolution , and recombination of
other
rare , inimitable and non - substitutable
resources . Assuming that these changed
resources [33] Heterogeneous and immobile
resources then used the resulting
organization's ability to obtain
their surroundings , importing various
scarce
strategic goals after investing substantial
subset of the organization's overall
such , organizations are investing more
support for not only financial
that humans are the primary
that the organization must control
no use , no benefits !
professionals . CityTrans report that
The
discussed earlier . However ,
we decided that
the change
the organization enhance the distinctive
the strategic purpose of IS
and IBM have invested
constant pressure to leverage
firm's focus and transforming
their
and to flexibly
Conclusion Firms should
reconfigure
their core competencies by leveraging
other stakeholders . Some
p . 101).
Tesco's regular
Use
of
these
the decision to build
use them . It is
to allocate mental and physical
to business performance and allocate
to locating and obtaining various
Value conceptualizes IS assets as
well as partners to provide
or
to use BI in
orchestration view [154] and / or
path
is a meaningful option
path 2 in panel
perspective on BI Assets , skilled
require an evaluation of data
requires huge amounts of information
signifies how an organization approaches
stems from RBV , the logic
such as differentiated knowledge contained
that
affect business processes , which
an organization must have
benefit organizations in creating
can enhance absorptive capacity
help organizations sustain competitive
in turn , deliver new
provide it with competitive
the resource - based view
The full set of resources ,
then used the resulting resources
to
achieve high BI assimilation .
analyze checkout data to
be returned as valued
building BAC . We conducted
conduct routine and nonroutine
design , produce and supply
implement BA systems , some
improve BA outcomes . This
make offers in its
produce
business value . The
value . The most
reduce cost [49,69] and
resolve imminent issues . Access
support analytics and deploy
tackle this issue systemically
towards high - return targets (H7)
were built , Tesco's regular use
when they need data to
will be the valuable , rare ,
with ineffective capital investments , inefficient
within the
focal organization to
organization as a
BI management capabilities Probabilistic processes
led to organizational benefits . The
• Collaboration from other groups • Customer

Semantic Network Diagram for label = Impact




decision - making and
Calculations Challenges
in
measuring
other metrics
outcomes , and then
Oliveira , and M.B . Ladeira ,“
Recommendations A Exhibit 5.1
regression splines to assess
research agenda for understanding
research can further explore
results , and to investigate
study to better examine
the research model examined
Business Analytics , explaining
the differential
comparable analytics resources ,
found to have
the highest
with individualism having
to be uncovered . Industry factors
user satisfaction , individual impact , organizational
workflow problems that will ultimately
on
decisions , customers , processes , or
incumbent IT investments as
organizational
innovation , followed by
value . Further , we
service innovation through discovery ,
the way
business is
decisions are
value creation . The intersection
or success of the outcomes .
Return on Investment (ROI) This
Table 3 . Exemplified Quotes from
targets In other words , what
that organizational resilience , absorptive capacity ,
the business . Although AP duties
to organizational performance .(Based on [
was the greatest , in terms
workshop OR56 Annual Conference , 911
• Profitability Return on assets • Equity

Semantic Network Diagram for label = Value